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Mobile Computing Device Adoption In Organizations: An Information-Processing Based View

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MOBILE COMPUTING DEVICE ADOPTION IN ORGANIZATIONS:

AN INFORMATION-PROCESSING BASED VIEW

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ABSTRACT

Mobile computing devices have gained popularity in organizations. Various companies, government agencies, and academic institutions have seen a dramatic increase in employees' adoption of personal mobile devices. Current research has not provided clear explanations about the motivations behind employees' mobile device adoption behavior and the factors affecting these behaviors. This paper proposes using a new perspective, an information-processing based view, to better understand this new trend. The newly developed measurement instrument, named as Information-Processing Support Index (IPSI), captures an employee's perceptions about the capabilities of mobile devices to support his/her work-related information-processing needs. An exploratory model using IPSI and other constructs to explain an employee's mobile computing device adoption intention is also explored. Overall, the IPSI instrument demonstrated acceptable levels of reliability, convergent validity, and discriminant validity. Based on empirical data collected from faculty and staff members in one large public university in China, after controlling for common method variance, this study found some support for four of five hypotheses, linking IPSI to an employee's mobile-computing-device-adoption intentions.

DEDICATION

I dedicate this dissertation to my family, especially, to my father, Dr. Aimin Guo; my mother, Ms. Qianru He; my father-in-law, Mr. Zhijun Li, my mother-in-law, Ms. Feng Lu; my wonderful wife, Yingying Li; and to my little angel, Victoria Guo.

Without your support, help, and understanding, I could not accomplish this work. I love you all so very much!

谨以此文献给我最最亲爱的家人，感谢你们对我的鼓励与支持，特别是：我的父亲郭爱民博士，母亲贺倩茹女士；我的岳父李志军先生，岳母卢凤女士；我温柔贤惠的妻子，李莹莹女士；还有我的小天使，郭玮琪宝宝。

没有你们的支持、付出和理解，就没有我现在取得的成绩。

我爱你们！

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CHAPTER I

INTRODUCTION

1. Background

In recent years, mobile computing technology has gone through a period of rapid development. Increasing integrated circuit chip density, as predicted by Moore's Law (Moore, 1965), makes mobile computing devices (smartphones, tablet computers, etc.) capable of performing complex computations, displaying stunning graphics, and connecting to the Internet. These devices are becoming an essential part of people's lives.

The mobile computing device market is expanding at a staggering rate. Global smartphone shipments reached 1 billion units in 2013 (IDC, 2013). The Online Publishers Association (OPA) indicates "44% of the U.S. Internet population, ages 8-64, owns a smartphone in 2012 (107 million consumers)", and that number was "expected to reach 57% by Q2 2013 (142 million consumers)" (OPA, 2012).

Similarly, the tablet computer market is also growing rapidly. For example, global tablet computer shipments were estimated to reach 100 million by 2012 (Morgan Stanley Research Global, 2011). In the meantime, global personal computer (PC) shipments suffered the first decline in a decade to 92.7 million in the fourth quarter of 2011 (Ricadela, 2012) and sales continued to drop to 76 million in the second quarter of 2013 (King, 2013).

These studies indicate that people are shifting their computing device preferences from PCs to mobile devices. In one study, 68% of smartphone owners reported that they could not live without their smartphones (OPA, 2012). The proliferation of these devices also marks a radical change in organizations' computing environments. Employees are beginning to adopt various mobile computing devices not only for personal uses, but also for work-related purposes (Holtsnider & Jaffe, 2012).

Consequently, the role of IT departments is changing from managing organizations' IT resources to providing IT support for employees. For example, according to Intel's Chief Information Security Officer (CISO) Malcolm Harkins, "since Jan. 2010, the number of employee-owned mobile devices on the job has tripled from 10,000 to 30,000", and by 2014 "... 70% of Intel's 80,000 employees will be using their own devices for at least part of their job" (Harkins, 2013). This trend of employees using their own mobile devices in the workplace presents new challenges and opportunities for organizations in many areas such as information security, communication management, operation efficiency, etc. (Hayes, 2012; Holtsnider and Jaffe, 2012; Messmer, 2012).

Studies have approached issues in mobile-computing-device adoption and management from different perspectives, e.g., End-User Computing (EUC) (Moore, et al., 2007), Consumerization of IT (Harris, et al., 2012; Holtsnider and Jaffe, 2012), and Human-Computer Interactions (HCI) (Hayes and Truong, 2013). However, most studies in marketing and behavioral sciences were focused on users' adoption behaviors (Schepman, et al., 2012), users' satisfaction with mobile devices/services (Kuo, et al., 2009), and design-related issues (Morris and Aguilera, 2012). These studies viewed mobile computing devices as 1) another high-tech consumer product; 2) a medium through which customers are consuming content such as mobile apps, news, video and music contents; and 3) a communication tool through which businesses can gain operating efficiency. Few scholars have examined why employees want to bring their own mobile devices to work. In the Management Information Systems (MIS) discipline, researchers observed similar trends in the 1970s and 1980s, when PCs first became available to individual employees (Dickson, et al., 1984). At that time, one big challenge organizations were facing was that employees were bringing their PCs to workplaces. As a result, organizations began to establish IT departments to manage their IT resources. Several studies focused on understanding how organizations could better manage their computing resources (Gurbaxani and Whang, 1999; Rockart and Flannery, 1983).

The current Bring Your Own Device (BYOD) trend is similar to the historic patterns of PC adoptions. However, some new characteristics distinguish mobile computing devices from PCs. For example, these devices are extremely easy to personalize; they are compact in physical size; and their operating systems differ greatly from each other (Pitt, et al., 2011). Therefore, the same set of factors that influenced PC adoptions will not be sufficient to address the BYOD trend. To date, there is a lack of research in the MIS field to guide companies to deal with this trend effectively. Furthermore, there is a lack of consensus among MIS researchers about why an employee wants to bring his/her own devices to workplaces, and why they choose to adopt different devices for work.

Researchers in the MIS field have focused narrowly on design features, mobile value-added services, or cognitive factors when studying mobile-computing-device adoptions (Rahmati & Zhong, 2013; Sarker & Wells, 2003). There is a need to systematiclly examine key factors that influence an employee's mobile-computing-device-adoption intentions in organizations.

2. Problem Statement

The current study has two underlying goals/contributions. First, this study proposes a new construct to capture how well mobile computing devices support an employee's job required information-processing activities. The new construct, Information-Processing Support Index (IPSI), focuses on two types of information-processing activities: content generation and consumption. Second, this study develops and validates a conceptual model of an employee's mobile-computing-device-adoption intentions. This study provides some initial insights about the research question: "Why and how does an employee choose to adopt different mobile computing devices in their work environments?"

Previous studies are missing one important aspect when explaining why an employee wants to adopt mobile computing devices: these devices can help people fulfill their work-related information processing needs. As discussed by Daft and Lengel (1986) and Galbraith (1974), one major way organizations use information systems (IS) is to help their information processing. Information systems can increase organizations' information processing capabilities or reduce their information-processing needs. Similarly, as important information system components, mobile computing devices can help an employee with his/her information-processing needs at workplaces as well.

A closer examination reveals two major types of information processing activities at workplaces: content generation and consumption. Content generation refers to information-processing activities that generate content/information for others. For example, writing a report, creating an email message, and performing an analysis all generate some content for others.

Content consumption refers to information-processing activities that consume content/information generated by others, for example, reading a report, reading an email, and making decisions among alternatives all require an employee to consume content. In organizations, people's jobs often require them to perform both types of information-processing activities. Chapter II provides a detailed discussion about these information-processing activities.

Since an employee's job requires him/her to engage in at least one of the two types of information-processing activities, mobile computing devices' capabilities to support these activities will greatly affect the employee's adoption intentions at workplaces. Therefore, the first step in this study is to develop a new construct, Information-Processing Support Index (IPSI) to capture how well mobile computing devices' capabilities support job-required information-processing activities. Once established, researchers can use IPSI to capture the factors driving an employee's technology adoption intentions at workplaces, especially their mobile-computing-device-adoption intentions.

In the next section, this chapter discusses definitions about mobile computing devices, and two component scores that are used to compute IPSI: Content Generation Score (CGS), and Content Consumption Score (CCS).

3. Mobile Computing Devices, CGS, and CCS

3.1. Definitions

In this study, mobile computing devices are devices that provide various computing capabilities while remaining small in their physical sizes. Three types of mobile computing devices are examined: smartphones, tablet computers, and laptop computers. A smartphone is a mobile phone built on a mobile operating system that provides capabilities in computational tasks and Internet connections. A tablet computer is a general-purpose mobile computer contained in a single unit that is capable of performing several computing tasks such as streaming video, browsing the Internet, sending/receiving e-mails. A tablet computer usually has a larger display than a smartphone (Ogg, 2010). A laptop computer is a type of personal computer that is lightweight and capable of performing a wide range of computing tasks. Other computing devices such as desktop computers, servers, etc. are not considered as mobile computing devices due to their lack of mobility.

When studying why people are adopting these mobile computing devices for work, researchers often find different explanations from different perspectives. For example, one former study identified familiarity with mobile computing devices and services as one of the reasons that people continued using their personal mobile devices at work (Schwarz, et al., 2004). However, studies also showed that people were not using their mobile devices for all types of tasks (OPA, 2012). Email was frequently cited as an indicator of mobile computing device usage, but few people used mobile computing devices for data analysis purposes (Gebauer, 2008). The difference between job requirements and devices' capabilities influences people's adoption intentions. Even when an employee is using more than one device at work (multi-screen users), they prefer different devices for different job requirements (OPA, 2012). These studies indicate that there is a need for developing a better instrument to capture factors that determine why an employee uses mobile devices at work.

The Morgan Stanley Research Global's study showed some insights about the differences in people's mobile-computing-device choices. They found that many consumers viewed tablet computers as an incremental device: 55% of potential tablet users did not expect a tablet to replace another technology product. In addition, their study used content creation and consumption to examine different capabilities of tablet computers (Morgan Stanley Research Global, 2011). As shown in Figure 1-1 and 1-2 below, people tend to use their tablet computers differently than their PCs.

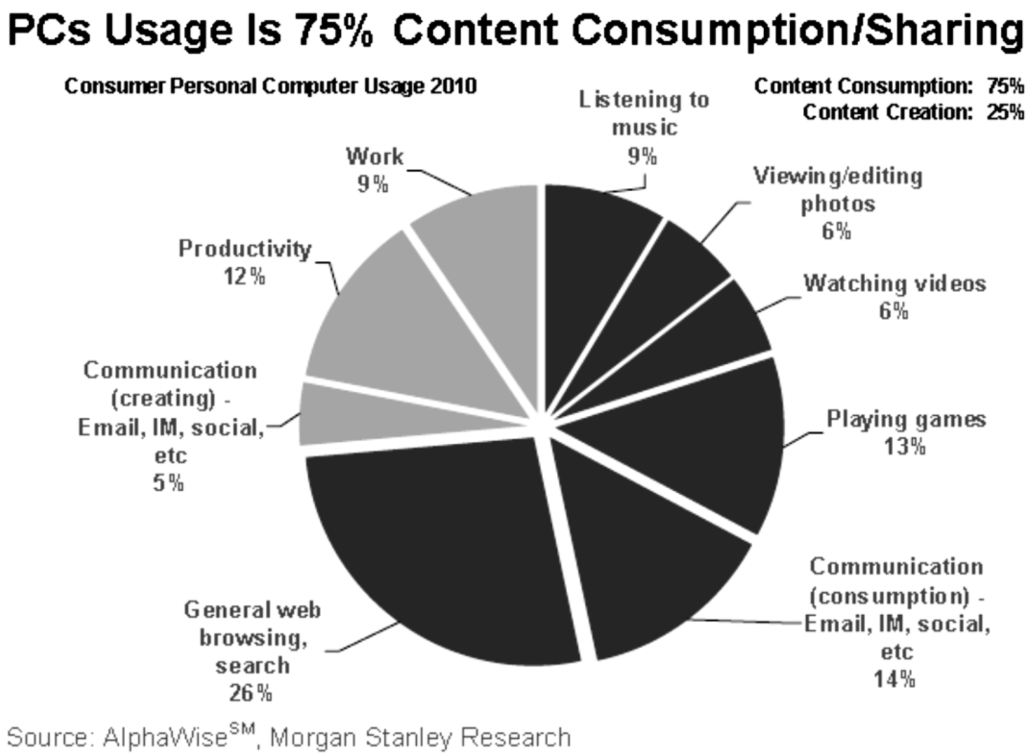


Figure 1-1. PCs' Usage (Morgan Stanley Research Global, 2011)

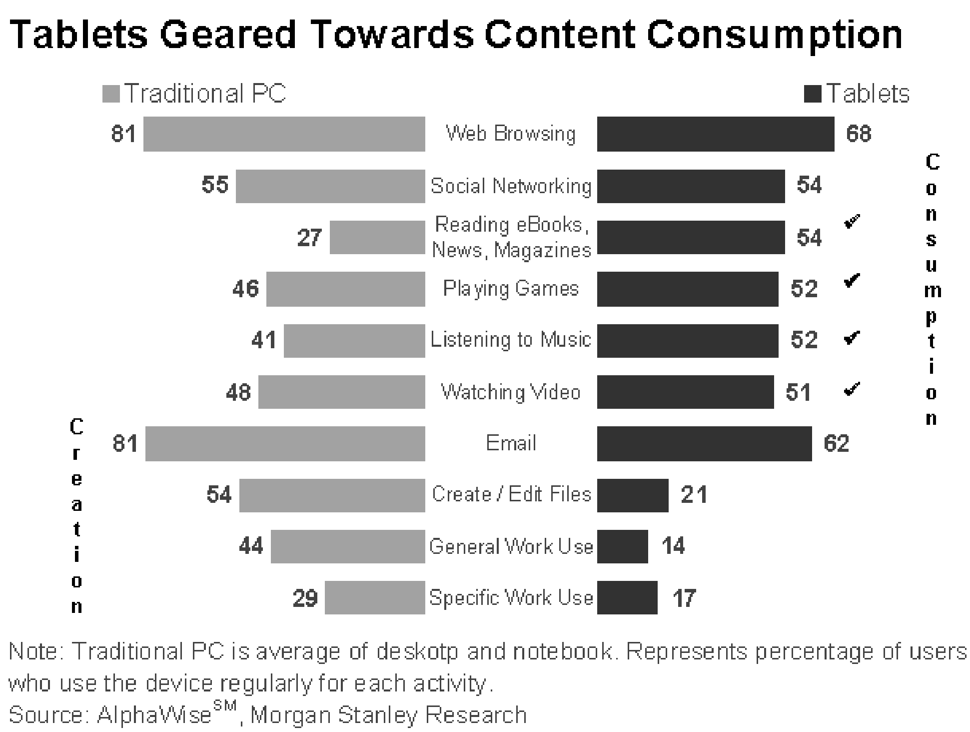


Figure 1-2. Tablet computer capabilities (Morgan Stanley Research Global, 2011)

The Morgan Stanley study focused on comparing consumer usage of traditional PCs (desktop and notebook computers) and tablet computers. Their results provided some observations about how employees use these devices differently. For example, Figure 1-1 shows that even when 75% of total PC usage is related to content consumption, most work-related usage is content creation. Figure 1-2 reveals that people frequently use tablet computers to consume content, while they use PCs more often to generate content. Therefore, since employees' jobs require them to engage in content generation and consumption differently, they are more likely to adopt devices that support their specific information-processing activities.

The IPSI framework developed in this study uses two aggregated scores to measure the degrees to which mobile computing devices can support content generation and consumption activities at workplaces: the Content Generation Score and the Content Consumption Score.

Content Generation Score (CGS) is a composite score used to measure the degree to which mobile computing devices' capabilities support job-required content-generation activities. These activities include gathering information, arranging information in different ways, and other information editing/generating activities. The CGS has two parts, CGS_{Device} and CGS_{Job}. They measure devices' capabilities to perform content generation activities and employees' job requirement in terms of content generation.

Content Consumption Score (CCS) is a composite score used to measure the degree to which mobile computing devices' capabilities support job-required content-consumption activities. These activities include not only receiving the information/content from others, but also acting on this information/content. Similar to the CGS, the CCS also has two parts: CGS_{Device} and CGS_{Job}, measuring devices' capability to fulfill content consumption and content consumption requirements in an employee's job.

Mobile computing devices have different capabilities to perform job-required content-generation/consumption activities. Tablet computers and smartphones can offer great capabilities to perform content-consumption activities such as reading news, email, and social network posts. However, primarily due to their size limits, they only possess limited capabilities to generate content. On the other hand, laptop computers have great content-generation capabilities such as creating/editing files, creating emails, and so on. However, due to larger sizes and weights, sometimes it is inconvenient to use laptops for just content-consumption activities.

As an example, in the electronic publishing industry, consumers (E-book readers) engage more in content consumption while publishers (E-book writers) engage more in content generation. In terms of their mobile devices usage, a reader is more likely to use a tablet to access E-books, and a writer is more likely to use a laptop to write E-books. The difference in their information processing needs leads to different device choices. This difference also exists among different levels of employees. For example, in comparison to lower-level employees, CEOs and other senior managers are more likely to use tablet computers at workplaces because their jobs require more content-consumption activities.

As discussed earlier, the CGS and CCS are not mutually exclusive. Mobile computing devices have both content-generation/consumption capabilities and an employee's jobs require him/her performing both activities as well. Therefore, mobile computing devices capabilities and job characteristics differ in the degree of content-generation and consumption capabilities/requirements. To account for this overlap, the proposed CGS and CCS are two continuous measurements. The next section briefly discusses how to categorize different mobile computing devices capabilities and job requirements in content generation and consumption. A detailed discussion and development of the IPSI framework and measures follows in Chapter II.

3.2. Mobile computing device capabilities:

Generally, mobile computing devices differ in their display sizes, operating systems, processing power, and input methods. Smartphones have the smallest sizes, limited operating systems, least processing power, and limited input methods. Laptop computers have the largest sizes, complete operating systems, most processing power, and most input methods. Tablet computers fall in between the other two. As a result, these devices have different capabilities to accomplish tasks related to content generation and consumption.

For example, in classrooms, students may use different mobile computing devices to help them with class-related activities such as taking notes, finding references, and sharing ideas. Depending on the specific task they need to perform, they will find these devices accommodate their needs differently. It is easy for a student to read assigned articles on his/her tablet computer; however, it is hard for the student to type the notes using the same device. As a result, vendors develop accessories such as Bluetooth keyboards to help the tablet computers with the content generation requirements. Students could attach these keyboards to their tablet computers to increase the tablet computers' capabilities in content generation when they need to fulfill their note-taking needs in classrooms. In other words, Bluetooth keyboards increase the CGS of tablet computers. In that way, these devices can better perform in tasks that have high CGS.

The proposed CGS and CCS measurements will capture these differences of mobile computing devices capabilities. They indicate how well devices support employees' information-processing activities in terms of content generation/consumption. In Chapter II, the IPSI framework uses the CGS_{Device} and CCS_{Device} to indicate how well these devices can perform in content generation/consumption activities.

3.3. Job Requirements

Employees' job requirements also differ greatly in terms of the degrees to which they require a person to generate/consume content. Higher-level managers such as CEOs, CFOs, and CIOs need to consume more content than lower-level employees do. Therefore, different positions within an organization require employees to deal with different tasks in terms of content generation/consumption. As a result, different mobile computing devices will accommodate these tasks differently. In Chapter II, the IPSI framework uses the CGS_{Job} and CCS_{Job} to indicate how frequently employees' jobs require them to engage in content generation/consumption activities.

Categorizing mobile computing devices characteristics and job requirements by content generation and consumption has two important implications:

1) It helps researchers understand why people bring these devices to workplaces. Since the design of most mobile devices focuses on content consumption, if employees' jobs require high level of information consuming, mobile computing devices rated high in CCS will help them with their jobs. For example, most of the CEOs' jobs require them to read and process various information generated by others. In this situation, they will benefit greatly from the use of mobile computing devices that have higher CCS. On the other hand, lower-level managers may still want to use their devices with a higher score in CGS, since large portion of their jobs requires them to generate content.

2) It helps managers to decide how to satisfy their employees' mobile computing needs. By comparing the CGS and CCS between employees' job requirements and mobile computing devices, managers can easily see how different mobile computing devices help employees in difference job situations. Overall, if managers can distinguish different types of mobile

computing devices in terms of their content generation and consumption capabilities, they can match those with employees' job requirements and provide employees with devices that support job-required information-processing activities better.

In the next section, a conceptual model is presented to explain how different factors influence an employee's mobile-computing-device-adoption intention at workplaces.

4. Model Constructs and Propositions

4.1. Information-Processing Support Index

As introduced above, the IPSI framework uses the CGS and CCS sub-scores to measure employees' job requirements and different mobile computing devices' capabilities. By comparing these scores, this study develops a direct measure about how well mobile computing devices support employees' job-required information-processing activities. To illustrate, Figure 1-3 shows the overall concept of the Information-Processing Support Index.

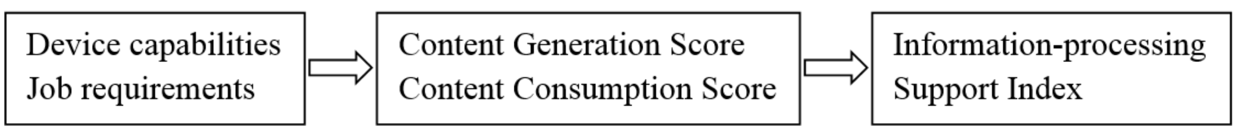


Figure 1-3. Information-Processing Support Index (IPSI) concept

By adopting the Task-Technology-Fit theory (TTF) of Goodhue and Thompson (1995), one of the reasons that employees use mobile computing devices is that they can get their jobs done more efficiently. If a mobile computing device's capability supports an employee's job-required information-processing activities, he/she is more likely to adopt that device for work. Based primarily on the TTF, the IPSI is defined as an index score measuring the levels to which mobile computing devices' capabilities support employees' job required information-processing activities. Developed in Chapter II, a higher IPSI score means mobile computing devices' capabilities support job required information-processing activities better. Therefore, the first proposition in the conceptual model is:

Proposition 1: IPSI has a positive relationship with an employee's mobile-computing-device-adoption intention.

4.2. Mobile-computing satisfaction

Various scholars have studied end-user satisfaction in the MIS field. Earlier works include the model of information systems success (DeLone and McLean, 2003), and end-user computing satisfaction (Doll and Torkzadeh, 1991). Doll and Torkzadeh (1988) defined end-user satisfaction as the positive opinion of a user about a specific computer application that they use. This study extends the definition of user satisfaction as the positive opinion of a user about a specific mobile computing device that they use. The conceptual model defines the mobile-computing satisfaction construct as the degree to which a person feels satisfied about his/her mobile computing needs.

DeLone and McLean (1992) stated that user satisfaction is one key measurement of information systems success, and user satisfaction with information systems is one critical criterion to evaluate systems success. User satisfaction with mobile computing information systems in the organizational environment largely depends on how well these systems help users with their jobs. Therefore, if capabilities of these devices meet/exceed employees' job requirements, employees will feel more satisfied. In addition, as stated in the TTF (Goodhue and Thompson, 1995), information technology is more likely to have a positive impact on individual performance and to be used if the capabilities of the IT match the tasks that the user must perform. Higher mobile computing satisfaction also leads to higher mobile-computing-device adoption intentions. Therefore, this study proposes a mediation effect of mobile-computing satisfaction in the conceptual model:

Proposition 2: Mobile-computing satisfaction mediates the positive relationship between IPSI and an employee's mobile-computing-device-adoption intention.

4.3. Mobile-computing dissatisfaction

Mobile-computing dissatisfaction is another construct in the conceptual model. The premise is that mobile-computing satisfaction and dissatisfaction are two independent factors regarding employees' perceptions about their mobile computing needs. As indicated by Herzberg's (1968) motivation-hygiene theory, job satisfaction and dissatisfaction act independently of each other. To motivate employees, organizations need to increase employees' job satisfaction or decrease their dissatisfaction. The mobile-computing satisfaction and dissatisfaction parallel that concept. However, mobile-computing dissatisfaction is not a hygiene factor. It acts differently from the mobile-computing satisfaction.

The expectancy disconfirmation paradigm (Anderson, 1973) in consumer satisfaction and dissatisfaction from marketing literature provided some suggestions about how user dissatisfaction affects employees' mobile-computing-device adoptions. For example, when people are using these devices, they will have expectations about the devices' performance. If the actual devices' performance falls below people's expectations, they will feel dissatisfied. For example, an employee may have adopted a tablet computer in the hope that it will help him/her to perform most job-related tasks. The tablet may support some tasks while not others. Therefore, depending on the initial expectations that an employee has and the actual capabilities of tablet computers, employees will have different degrees of dissatisfaction.

People also have general expectations about whether their organizations allow them to use their mobile computing devices at work. For example, Loose, et al. (2013) have studied employees' expectations and attitudes towards BYOD and found that allowing personal mobile device usage in workplaces can be a powerful way to recruit future employees. In their conclusions, when people were considering new jobs, they tended to view being able to have their own mobile devices as a more attractive offer. Therefore, providing the opportunity to bring these devices to work may reduce employees' dissatisfaction about their mobile computing needs.

In this study, mobile computing dissatisfaction is the degree to which a person feels dissatisfied about his/her mobile computing needs. If a mobile computing device's capability supports a person's job-required information-processing activities, he/she is less likely to feel dissatisfied about his/her mobile computing needs. Therefore, a higher IPSI score will decrease mobile computing dissatisfaction at workplaces. The lowered mobile computing dissatisfaction will lead to higher device adoption intentions. In the conceptual model, this study proposes a mediation effect of mobile computing dissatisfaction:

Proposition 3: Mobile-computing dissatisfaction mediates the positive relationship between IPSI and an employee's mobile-computing-device-adoption intention.

4.4. Social influence

The social environment and influence from others also affect employee's adoption of mobile computing devices. In the unified theory of acceptance and use of technology (UTAUT), Venkatesh, et al. (2003) defined social influence as the degree to which an individual perceives that important others believe he or she should use the new system. They incorporated three dimensions into their model: subjective norm, social factor, and image.

They adopted the definition of social factor as the individual's internalization of the reference group's subjective culture, and specific interpersonal agreements that the individual has made with others, in specific social situations (Thompson et al., 1991). The definition of image they used was the degree to which use of an innovation is perceived to enhance one's image or status in one's social system (Moore and Benbasat, 1996). Both dimensions are relevant to discussions about mobile-computing-device adoption. For example, one of the mobile computing device's characteristics is that an employee can carry these devices around and others will link social status and organization norms to their use. Therefore, perceived norms and image that arise from using mobile computing devices will affect an employee's adoption intention.

Studies in the impression management area also provided some evidence that the social factor affects an employee's mobile-computing-devices-adoption intention. Impression management is concerned with the behavior people direct toward others to create and maintain desired perceptions of them (Gardner and Martinko, 1988a; Schneider, 1981). Most studies in the field of impression management focus on face-to-face interactions (Gardner and Martinko, 1988b; Goffman, 1959). However, mobile computing devices also play an important role in people's impression management attempts. For example, by using mobile computing devices, people can reply to work-related email messages instantly, creating an impression that they are always available and responsive to requests. On the other hand, due to the limited editing functionalities of some mobile computing devices, people are less inclined to use these devices when they are dealing with important email messages. In such situation, an employee wants to send carefully constructed messages to maintain his/her professional impression to others.

As Caron, et al. (2013) found out, executives exhibit different ways of using email on their smartphones than on their office computers. They tend to be more informal regarding the use of email on their smartphones. Mobile computing devices represent new ways through which people can interact with others, project their visions, and influence workplaces norms. Employees' needs to manage their impressions also affect their mobile-computing-devices-adoption intentions.

As discussed above, this study defines social influence as the influence mobile computing devices have at workplaces. It includes three dimensions: perceived norms about using mobile computing devices, perceived social status represented by mobile computing devices, and mobile computing devices' capabilities to influence others' impressions.

This dissertation focuses on the overall effect social influence has on people's mobile-computing-device-adoption intentions. The more social influence mobile computing devices have, the more likely an employee will be to adopt them. In the conceptual model, this study proposes a positive relationship between social influence and an employee's device adoption intention:

Proposition 4: Social influence of mobile computing devices has a positive association with an employee's mobile-computing-device-adoption intention.

4.5. Mobile computing self-efficacy

Many studies of self-efficacy have their roots in social cognitive theory (SCT), which is a widely accepted theory of individual behavior (Bandura, 1977). Bandura (1986) defined self-efficacy as people's judgments of their capabilities to organize and execute courses of action required to attain designated types of performances. It is concerned not with the skills people have but with judgments of what people can do with whatever skills they possess. Based on that, Compeau and Higgins (1995) defined Computer Self-Efficacy (CSE) as "an individual judgment of one's capability to use a computer" (p. 192).

Various researchers suggested that CSE plays a significant role in an individual's decision to use computers (Compeau, et al., 1999; Marakas, et al., 1998). Discussions about CSE also apply to mobile computing devices. Some scholars have tried to define and test the construct of mobile computing self-efficacy (MCSE). For example, Wang and Wang (2008) developed a 45-item instrument for MCSE. Their instrument contained five dimensions: using basic mobile computer operations, general use of the Internet, using e-mail, using specific mobile services, and accessing/understanding mobile computer knowledge. While they celebrated the validity and reliability of their instrument, it focused narrowly on usage of email and the Internet and was too long to adopt for this dissertation.

After examining relevant literature, this study defines the MCSE construct as an individual judgment of one's capability to use mobile computing devices. People who have higher MCSE will hold the perception that they are more capable of using these devices. As a result, they are more likely to adopt these devices for work. In the conceptual model, this study proposes a positive relationship between MCSE and people's mobile-computing-device-adoption intentions:

Proposition 5: An employee's Mobile Computing Self-Efficacy (MCSE) has a positive association with his/her mobile computing-device-adoption-intention.

5. The Conceptual Model

Figure 1-4 below illustrates the overall conceptual model developed in this study. The solid lines indicate positive relationships while the dashed lines indicate inverse relationships. The five major constructs in the model are the Information-Processing Support Index (IPSI), mobile computing satisfaction, mobile computing dissatisfaction, social influence, and Mobile Computing Self-Efficacy (MCSE). IPSI, social influence, and MCSE positively affect employees' mobile-computing-device-adoption intentions. Employees' mobile-computing satisfaction and dissatisfaction mediate the positive relationship between IPSI and employees' adoption intentions.

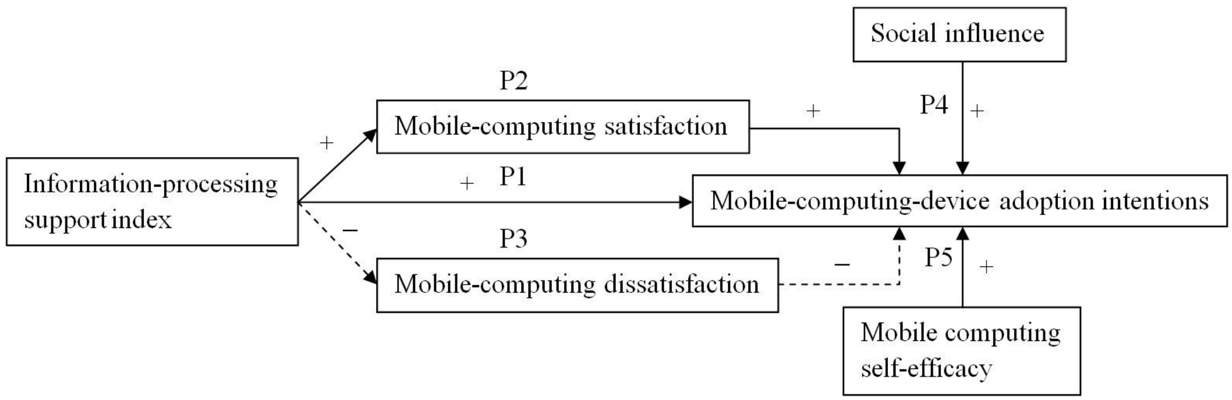


Figure 1-4. Conceptual model of mobile-computing-device-adoption intentions

6. Proposed Methodology

This study investigates factors affecting people's mobile-computing-device-adoption intentions at workplaces. The data analysis aims at providing empirical support for the proposed conceptual model and propositions. One of the primary contributions of this study is the IPSI framework because it can be used to assess how well mobile computing devices support employees' information-processing activities.

Following Churchill's (1979) guidelines of scale development and the domain-sampling model (Nunnally and Bernstein, 1994; Peter, 1979), this study takes the steps of domain specification, sample item generation, and measurement refinement to develop a new multi-item instrument for IPSI. Since this is a preliminary study, it limits the type of organizations examined to educational institutions. By focusing on only educational institutions, this study achieves the following benefits:

First, focusing on one type of organization helps to eliminate organizational differences. Therefore, there will be less “noise” in assessing the measurement model. Second, educational institutions are at the frontier of educating future employees. The massive adoption of mobile computing devices in educational settings is an unavoidable trend. Therefore, insights gained through this study will help these institutions to manage those devices more effectively. Third, although organizations differ from each other, they share the same information-processing concept. Therefore, using only educational institutions will have minimal effects on the generalizability of findings about the IPSI using CGS and CCS.

Instrument Generation

After a review of related literature, the measurement model in Chapter III specifies independent variables, dependent variables, and testable hypotheses. In this study, a new instrument of IPSI using the CCS and CGS is generated, refined, and validated. Chapter III operationalizes all other constructs through adopting well-developed instruments from relevant literature. Finally, the validity and reliability of the study’s instruments are tested in the pilot and main study.

Instrument Refinement and Pilot Study

The newly generated IPSI instrument was refined by a Q-sort test. Then a pilot study was conducted to assess reliability, convergent validity, and discriminant validity of the survey instruments. The respondents in the pilot study were undergraduate students. Cronbach’s alpha coefficients were used to assess the reliability of these instruments and a Confirmatory Factor Analysis (CFA) was performed to examine the convergent and discriminant validity. Cross-loaded items or items that fail to load properly were revised or dropped from the final survey instrument. The pilot study also provided preliminary results about the hypotheses testing in the measurement model. After the pilot study, the main study collected data for further analyses.

Main Study

The main data collection was conducted at one large public university in the central part of China. The main study serves two purposes: validating the measurement model and providing empirical results concerning the propositions in the conceptual model. The Chinese university launched a program to provide its 1,800+ employees with smartphones of their choice. The program provided fourteen types of smartphones, with operating systems ranging from iOS, Android, to Windows Phone 7.5/8. This is the university's recent attempt to manage its employee-owned mobile devices at work.

In this program, all employees were given the opportunity to choose their own mobile computing devices (smartphones), and use it for both personal and work purposes. These smartphones serve as the primary contact media through which the university notifies its employees about work-related issues. Employees cannot change the SIM cards in these smartphones. Therefore, they have to use these devices for work. This is a great opportunity to study how and why people choose different mobile computing devices at workplaces. Paper based survey instruments were distributed to employees at the university.

CFA and Cronbach's alpha was used to ensure the validity and reliability of the instruments. The measurement model was tested as a whole for its significance and each hypothesis was tested individually using multiple regression and structural equation modeling (SEM) techniques. Chapter III discusses methodological issues and the data analysis methods in more detail.

7. Chapter Summary

Mobile-computing-device adoption and management at workplaces is an emerging issue. This study proposes a new way of studying this issue from people's information-processing needs. A new construct, the Information-Processing Support Index using the CGS and CCS measurements, developed in this study, captures how well mobile devices' capabilities support employees' information-processing activities in terms of content generation and consumption. This study proposes a conceptual model of mobile computing-device-adoption intentions at workplaces including the Information-Processing Support Index (IPSI), mobile computing satisfaction, mobile computing dissatisfaction, social influence, and Mobile Computing Self-Efficacy (MCSE).

This chapter provided an overall introduction of background information, research question, and the conceptual model. Chapter II reviews relevant literature, and develops the conceptual model. Chapter III discusses the model operationalization and research methodology issues. Chapter IV discusses the instrument refinement and data analysis. Chapter V discusses issues in the main study data analysis. Finally, Chapter VI concludes this study and provides some discussion about future research directions.

CHAPTER II

LITERATURE REVIEW

1. Chapter Overview

This chapter provides a detailed review of literature related to the conceptual model developed in this study. The literature reviewed covers consumerization of IT, information-processing view of firms, task-technology fit theory, end-user satisfaction and dissatisfaction, unified theory of acceptance and use of technology, impression management, and mobile-computing self-efficacy.

The first section of this chapter focuses on developing the Information-Processing Support Index (IPSI) framework. After reviewing current literature about consumerization of IT, this chapter identifies gaps about employees' mobile-computing-device adoptions. The IPSI, which is developed from information-processing view of firms, provides an index score indicating how well employees perceive mobile computing devices can support their job-required information-processing activities. This is an important first step in explaining an employee's mobile-computing-device-adoption intention from the information-processing perspective.

In the next section, this chapter reviews literature about Task-Technology Fit theory (TTF) and end-user satisfaction/dissatisfaction. As the Technology-to-Performance Chain (TPC) model (Goodhue and Thompson, 1995) predicts, precursors of utilization such as user's attitudes mediate the effect of TTF on utilization of technology (p.217). This study identifies mobile-computing satisfaction and dissatisfaction as two independent mediators between the IPSI and employees' mobile-computing-device-adoption intentions.

Finally, this chapter reviews literature about social influence and Mobile Computing Self-Efficacy (MCSE). Drawing from the unified theory of acceptance and use of technology (UTAUT) and the impression management literature, the social influence construct in this paper contains three dimensions: perceived norms about using mobile computing devices at workplaces; perceived social status represented by mobile computing devices; and mobile computing devices' capabilities to influence other people's impressions. The MCSE construct has its root in social learning theory and computer self-efficacy.

2. Information-Processing Support Index

The following section develops the Information-Processing Support Index (IPSI) construct. First, literature in the area of consumerization of IT provides evidence that managing the increasing number of mobile computing devices brought to work by employees is an important issue. Organizations are just starting to catch up with this massive trend of Bring Your Own Devices (BYOD).

2.1. Consumerization of IT and Mobile Device Management (MDM)

As introduced in Chapter I, the increasing power of mobile computing devices makes them capable of performing a wide range of work-related tasks. Employees are beginning to bring their own mobile computing devices to workplaces (Holtsnider and Jaffe, 2012). Consequently, organizations face the challenge of shifting their focus from controlling/managing their computing resources to providing IT service/support for their employees. Studies have shown that organizations were trying to adapt to this new trend by designing mobile device management policies at workplaces (Messar, 2012; Steinert-Threlkeld, 2011). Researchers in the

MIS discipline refer to the trend that employees want to bring their consumer information technology (IT) such as devices, applications, and services into corporate environment as the “consumerization of IT” (Niehaves et al., 2013).

As discussed by Loose, et al. (2013), BYOD is a sub-trend of consumerization of IT that focuses on devices, which allows employees to incorporate their own mobile devices into organization network infrastructures. Shim, et al. (2013) discussed several potential benefits of BYOD, including familiarity and satisfaction of using employee’s choice of devices, and money-savings on devices and data plans from the organizations' perspectives. Organizations want to use BYOD to increase flexibility, convenience, and portability of devices that cater to the employee’s workflow, which increases employees’ productivity and morale (Harris, et al., 2012).

Current research on BYOD has focused on organization-level adoption, performance gains, and security issues (Messer, 2012; Niehaves, et al., 2012). Thomson (2012) discussed issues about employees using their personal mobile devices at workplaces. He suggested that BYOD is an inevitable trend. However, there is a lack of understanding and practice among managers about how to manage these devices at workplaces efficiently. Organizations need to adapt their mobile devices management practices in this new trend.

The Mobile Device Management (MDM) concept describes solutions that facilitate the remote management of mobile devices (Wong, 2008). In current literature, researchers are just beginning to view mobile computing devices (smartphones and tablet computers) as important personal information systems. Few researchers have examined mobile-computing-device adoption at workplaces from the individual level. Especially, there is a lack of research about what types of mobile computing devices an employee needs based on his/her job requirements and how differences in mobile devices affect an employee's mobile-computing-device adoption in an organization's computing environment.

Pitt, et al., (2011) proposed a framework to categorize information interactions on information system devices with regard to the presence or absence of user input or device output. They also used the context for these interactions to provide guidelines about when to use these devices (tablet computers) for business applications. Their information interaction framework provided some insights about how people's jobs require them to interact with information systems. However, their discussions focused on organization-level adoptions. Therefore, the manner in which informational interactions and context affect individual employees' mobile-computing-device choices is still unclear.

Ortbach, et al. (2013) discussed the individualization process with respect to IT consumerization. Their study acknowledged the lack of research about antecedents of IT consumerization, especially at the individual level. In their framework, individual information systems contain personal activity systems and professional activity systems. The expected performance improvement and the consumerization behavior of coworkers both have positive effects on individual's consumerization intentions. Although they were able to explore some individual-level factors affecting the mobile-computing-device adoption at workplaces, their work was unable to explain more fundamental reasons that employees want to adopt these devices. To fill this gap, this dissertation looks into the literature of information processing and views mobile-computing-device adoption through the lens of information-processing activities.

2.2. Information processing view of firms

Current studies about IT consumerization and BYOD take perspectives from human computer interaction (Schwarz et al., 2004), work-life balance (Yun, et al., 2012), and innovation diffusion (Ratten, 2010). One important aspect is missing: how mobile computing devices support employees with their job-required activities. Gebauer (2008) indicated that employees adopting these mobile computing devices were expecting performance gains through better connectivity, real-time access to resources, and flexibility of time management. However, his study focused only on smartphones and personal digital assistants (PDAs) with limited functionality at the time when it took place. He provided some insights about categorizing tasks into general business tasks and technology with a focus on managers, which limited the range of tasks considered.

Instead of focusing on particular technology support (e.g., mobile email) or particular users (e.g., managers), this study focuses on the more general technology support mobile computing devices provide to all employees. Since all employees in an organization will engage in information-processing activities, this study proposes that mobile computing devices' capabilities to support information-processing activities influence an employee's mobile-computing-device-adoption intention at workplaces. The information processing view of firms by Galbraith (1974) provided theoretical foundations for this proposition.

The information processing view of firms holds that from an organization design perspective, all organizations process information in order to function. Gathering, processing, and acting on data from the environment is an organization's main task (Daft and Weick, 1984). The amount of information that needs to be processed depends upon the level of uncertainty. Following that idea, Daft and Lengel (1986) proposed that uncertainty and equivocality are the two factors that determine an organization's information-processing structure.

Studies have utilized the information processing view to explain why organizations have different structures, communication channels, and norms of IT usage (Mani, et al., 2010;

Melville and Ramirez, 2008). This study treats a mobile computing device as a special type of individual information system. Although the information processing view is simple and important, few study have examined individual-level information processing at workplaces and how that leads to different mobile device choices.

By extending the information processing view of firms, this study proposes that employees' jobs require them to process information. The ability to process information will affect employees' performance. To support that proposition, as indicated by the Information Technology Associates' (ITA) dictionary of occupational titles (DOT), every job requires a person to function to some degree in relation to data, people, and things. The DOT used a 9-digit occupational code to distinguish different job titles. As shown in Table 2-1 below, the middle three digits of the code are the worker functions ratings of the tasks performed in the occupation. Generally, employee functions involving more complex responsibility and judgment have lower numbers while functions that are less complicated have higher numbers in the table (ITA, 1991).

Data (4th Digit)	People (5th Digit)	Things (6th Digit)
0 Synthesizing	0 Mentoring	0 Setting up
1 Coordinating	1 Negotiating	1 Precision Working
2 Analyzing	2 Instructing	2 Operating-Controlling
3 Compiling	3 Supervising	3 Driving-Operating
4 Computing	4 Diverting	4 Manipulating
5 Copying	5 Persuading	5 Tending
6 Comparing	6 Speaking-Signaling	6 Feeding-Off Bearing
7 Serving	7 Serving	7 Handling
	8 Taking Instruction-Helping	

Source: Dictionary of Occupation Titles (1991)

Table 2-1. Occupational digits expressing a job's relationship to data, people, and things

This list demonstrates not only how people's job requirements differ from each other, but also how people's jobs require them to engage different information-processing activities. For example, employee functions involving more complex responsibility and judgment will require an employee to analyze larger amount of information. The data dimension is straightforward: synthesizing data requires an employee to process more information than simply serving data. Similarly, in the people and things dimensions, mentoring people and setting up tasks require an employee to process more information than taking instructions from people and handling tasks. Therefore, the information processing view of people's job requirements predicts that the more complex job requirements are the more information processing an employee needs to perform.

A further analysis of these job requirements and information processing reveals that there are two major types of information-processing activities when people are performing their job functions: content-generation and consumption. As introduced in Chapter I, all employees need to generate and/or consume content at work. Content-generation and consumption capture the different information flows at the individual level. The information flows primarily outward from the employee in content-generation activities while in content-consumption activities information flows primarily inward to that employee.

Different job requirements, as discussed earlier, will have different demands in terms of these two types of information-processing activities. On the other hand, different mobile computing devices have different capabilities to perform these information-processing activities as well. Therefore, capturing differences between the perceived device capabilities and job requirements will help researchers explain why people in different jobs choose to adopt different mobile computing devices at workplaces.

This study develops the Information-Processing Support Index (IPSI) to capture how an employee perceives mobile computing devices as being capable of supporting his/her jobs in terms of content-generation and consumption. Based on the ideas from the information processing view of firms, the IPSI measures perceived mobile computing device capabilities and job required information-processing activities using the Content Generation Score (CGS) and the Content Consumption Score (CCS).

2.3. Content Generation Score and Content Consumption Score

The content-generation and consumption activities are not mutually exclusive. Mobile computing devices can support both activities. The CGS and CCS measurements in the IPSI framework are two composite measures varying in the same scale.

In today's business environment, content-generation activities are essential in people's daily jobs. Employees have to generate content if they want to communicate with others. In this study, content-generation activities include not only activities that create new content, but also those that communicate content to others. For example, creating a business report, giving a training session, and inputting data for performance dashboards all require employees to generate content. Therefore, the CGS is an aggregated score to assess first, how well perceived mobile computing devices capabilities support content-generation activities; and second, how much content-generation an employee's job requires him/her to perform.

Another important part of people's jobs is to receive, analyze, and use content from other sources. From newspapers to televisions, from Internet websites to mobile apps, technology is shaping the way people consume content every day. In this study, content-consumption activities at workplaces refer to receiving and using content from others. For example, reading a business report, receiving a training session, and monitoring a performance dashboard all require employees to consume content. Similarly, the CCS is an aggregated score to assess one, how well perceived mobile computing devices capabilities support employees' content-consumption activities; and two, how much content-consumption an employee's job requires him/her to perform.

The difference between perceived device capabilities and job requirements surrounding the two information-processing activities provides a fundamental way to explain why people choose different mobile computing devices at workplaces. As this study proposes, one of the reasons that employees choose to use mobile computing devices at workplaces is that these devices help them perform their job functions. Depending on different job requirements, different mobile computing devices are preferred when employees think their capabilities can better support job-required information-processing activities.

The following section discusses how the IPSI measures perceived device capabilities and job requirements using the CGS and CCS to form a composite measure of individual-level information processing at workplace.

2.4. Information-Processing Support Index

The IPSI indicates how well employees perceive mobile computing devices can support job-required information-processing activities. As discussed above, the IPSI uses two sub-scores, CGS and CCS, to capture this information.

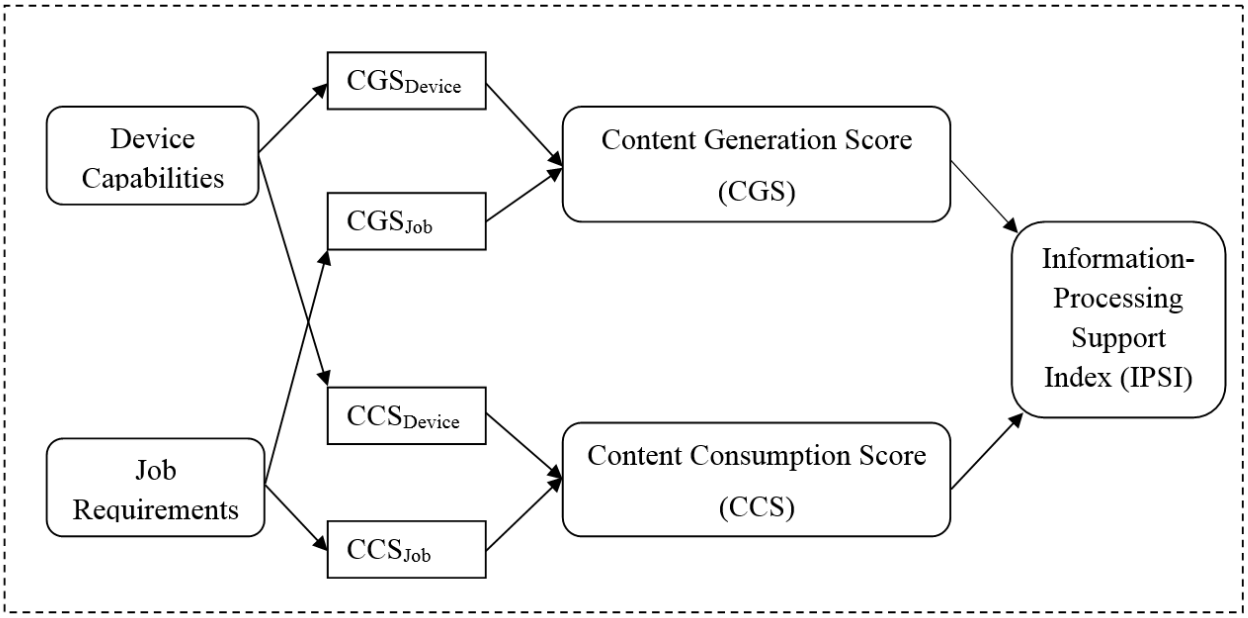
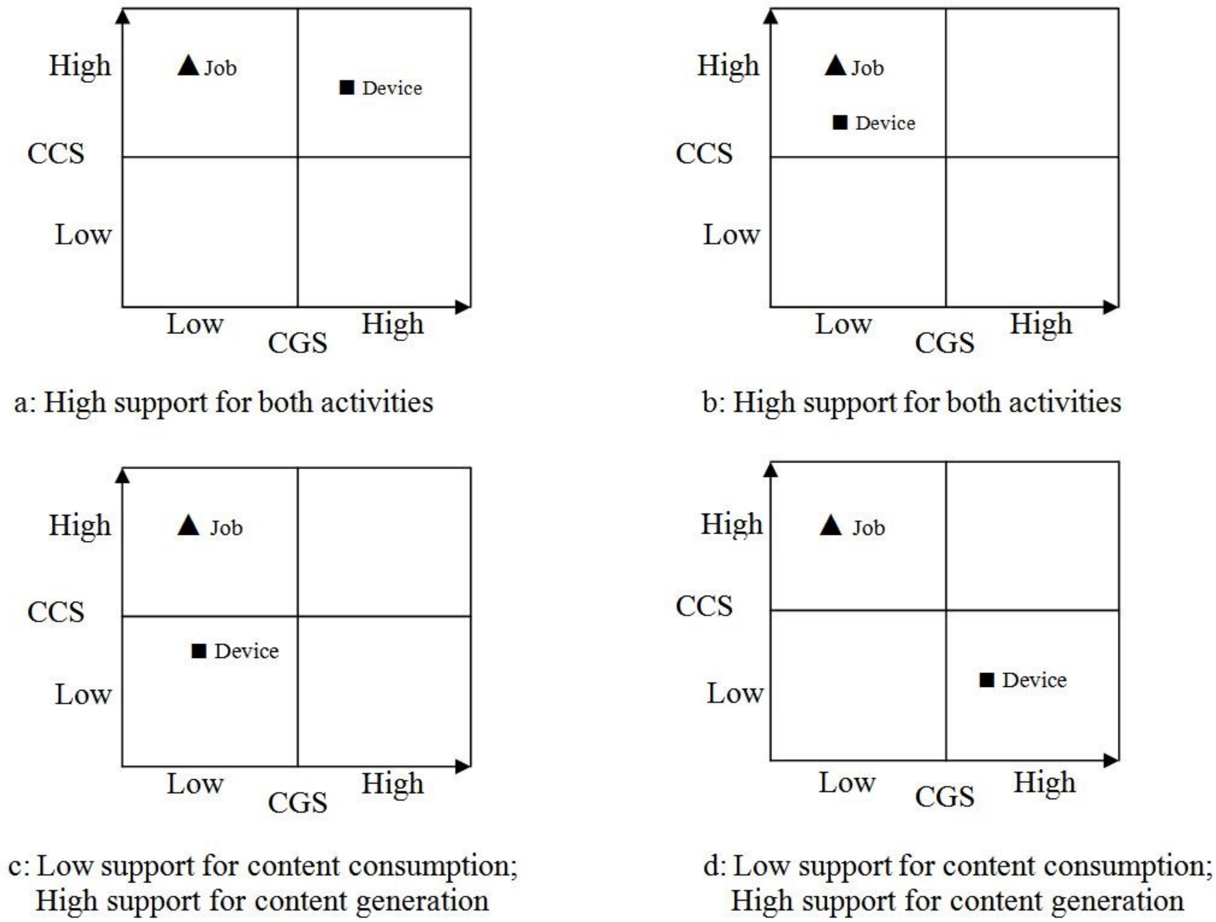


Figure 2-1. Information-Processing Support Index (IPSI) framework

As demonstrated in Figure 2-1, the CGS_{Device} and CCS_{Device} measure the perceived mobile computing device capabilities to perform content-generation and consumption activities. The CGS_{Job} and CCS_{Job} measure how frequently employees' jobs require them to perform these activities. By comparing the two sets of CGS and CCS measures on device and job requirement, the IPSI framework captures the reason that employees have different perceptions about how well mobile devices can support their job. Since both scores vary on the same scale, there are several possible combinations when comparing these scores. Figure 2-2 below shows some examples of the possible combinations when comparing these scores.



a: High support for both activities

b: High support for both activities

c: Low support for content consumption; High support for content generation

d: Low support for content consumption; High support for content generation

Figure 2-2. Examples of CGS/CCS measures

In Figure 2-2, if the job requirement has a low CGS_{Job} and a high CCS_{Job}, this means that the job requires employees to perform content-generation activities less frequently and content-consumption activities more frequently. Therefore, mobile computing devices support this job differently depending on their capabilities to support these activities. The mobile device in Figure 2-2a has high scores in both CGS_{Device} and CCS_{Device}, meaning that it has high perceived capabilities in performing both content-generation and consumption tasks. The device in Figure 2-2b has a low score in CGS_{Device} and a high score in CCS_{Device}, meaning that it has low perceived capabilities in performing content-generation tasks and high perceived capabilities in performing content-consumption tasks. The device in Figure 2-2c has low scores in both CGS_{Device} and CCS_{Device}, meaning that it has low perceived capabilities in performing both content-generation and consumption tasks. The device in Figure 2-2d has a high score in CGS_{Device} and a low score in CCS_{Device}, meaning that it has high perceived capabilities in performing content-generation tasks and low perceived capabilities in performing content-consumption tasks. Therefore, employees perceive mobile devices in Figure 2-2a and 2-2b having capabilities to better support the job required information-processing activities than those in Figure 2-2c and 2-2d.

Generally, mobile computing devices are unable to fulfill all of an employee's information-processing needs at workplaces when these devices' perceived capabilities fall below the employee's job requirements in CGS and/or CCS. In that situation, that employee is not likely to use these devices at work. Therefore, the bottom line for an employee to adopt these devices at workplaces is that these devices must have capabilities that meet or exceed the employee's job requirements in terms of content-generation and consumption.

When comparing perceived device capabilities with job requirements using the CGS and CCS, there are three scenarios:

1) Devices fail to support job-required information-processing activities:

The mobile computing device's capabilities fall below job requirements in at least one of the CGS and CCS. In this case, the mobile computing device fails to support the employee's job requirements in content-generation and/or consumption. The IPSI assigns a score of less than 1 to denote that the device fails to support relevant information-processing activity(s) at the minimum level.

2) Devices provide just enough support to fulfill job-required information-processing activities:

The mobile computing device's capabilities match the job requirements in the CGS and CCS. In this case, the mobile computing device is just capable of supporting the employee's job requirements in content-generation and consumption. The IPSI assigns a score of 1 to denote that the device is able to support relevant information-processing activity(s) at the required level.

3) Devices provide support beyond the necessary job-required information-processing activities:

The mobile computing device's capabilities exceed at least one of the job requirements in the CGS and CCS. In this case, the mobile device has capabilities that exceed at least one of job requirements in terms of content-generation and consumption. Therefore, the mobile computing devices support employees' job better than the devices in other two scenarios. The IPSI assigns a score of greater than 1 to denote that the device supports relevant information-processing activity(s) exceeding the minimum required level. Chapter III discusses formulas for calculating these IPSI framework scores in more detail.

The IPSI framework presented above provides a powerful way of capturing differences in perceived device capabilities and job requirements. Chapter III develops specific instruments for the IPSI including the CGS and CCS sub-scores. As indicated in the conceptual model, employees tend to adopt mobile computing devices that have higher IPSI scores. In the MIS literature, studies of the Task-Technology-Fit theory (TTF) (Goodhue and Thompson, 1995) provided additional theoretical support for this proposition.

3. Task-Technology-Fit Theory

In the model of PC utilization, Thompson et al. (1991) suggested that one of the factors affecting people's PC usage intentions is the capability of a PC to enhance an individual's job performance. They defined that as perceived job fit, which measures the extent to which an individual believes that using a PC can enhance the performance of his or her job (p. 129). Their job-fit construct captured the overall fit of technology regarding employee's tasks. They did not distinguish different activities an employee's job can require him/her to perform.

Goodhue and Thompson (1995) in their TTF theory suggested that information technology is more likely to have a positive impact on individual performance and to be used if the capabilities of the IT match the tasks that the user must perform. Focusing on employees' job performance and technology utilization, the TTF model examined the fit between task characteristics and technology characteristics and the linkage between the fit and technology utilization. The TTF theory is one of the most widely-used theories when examining technology adoptions in organizations.

Various researchers have adopted the TTF theory in their studies. Pagani (2006) used the TTF in combination with Technology Acceptance Model (TAM) (Davis, 1989) to study adoption of high-speed data services in the business market. His study provided support for the TTF model and suggested technology adoption depended partially on how well the new technology fits the requirements of a particular task (p. 848). His study focused on the context of high-speed data service adoption and included specific measures in that context. By surveying a large number of companies across the US and five countries in Europe, he found the combined TTF/TAM predicts the intention to adopt. However, his study still focused on organization-level adoption measures.

Liu, et al. (2011) extended the TTF into a three-dimension Task-Individual-Technology Fit construct: individual-technology fit, task-individual fit, and task-technology fit. They suggested that different dimensions of fit would affect performance directly or indirectly through user attitudes. Following these ideas, Parkes (2013) examined how the fit among individual difference, technology, and task affected people's performance and attitude toward technology. Her study focused on the decision-making context and divided the performance into two dimensions: using the system and using the outputs of the system. Both studies utilized controlled lab experiments for their statistical analysis and generally confirmed the linkage between fit and performance.

Most of studies utilizing TTF theory focused on organization-level information systems adoptions. Depending on specific task orientations, they usually have specific task contexts. In this study, the TTF theory provides theoretical foundations for the IPSI construct. However, this study focuses on an individual employee's mobile-computing-device-adoption intention with more general measures about perceived device capabilities and job requirements. By utilizing the CGS and CCS, this study captures the perceived level of support mobile computing devices can provide to an employee's job required information-processing activities. This study provides some initial insights and measurable constructs about how perceived mobile device capabilities and an employee's job requirements affect his/her device choices. This is the first attempt to explain individual-level IS adoption intentions from information-processing perspective.

In the conceptual model, other factors also influence an employee's mobile-computing-device-adoption intensions at workplaces. Previous literature about end-user satisfaction and dissatisfaction suggested two important mediators between IPSI and an employee's mobile-computing-device-adoption intentions.

4. Mobile-Computing Satisfaction and Dissatisfaction

One of the direct subsequent constructs the TTF suggested is user satisfaction. For example, Aiken, et al. (2013) discussed the linkages between TTF and user satisfaction. Higher fit between employees' task requirements and mobile technology capabilities often leads to higher user satisfaction.

In the conceptual model developed in this dissertation, mobile-computing satisfaction and dissatisfaction are two factors mediating the positive relationship between the IPSI and employees' mobile-computing-device-adoption intentions. In this study, satisfaction and dissatisfaction are proposed as two independent factors. Mobile-computing satisfaction stems from the larger concept of end-user satisfaction in the MIS literature.

4.1. Mobile-computing satisfaction

In the MIS literature, Rockart and Flannery (1983) categorized end-users into six different types. They discussed the idea of managing end-user computing by providing different support. As technology advances, end-users are using more and more computing resources in organizations. Their satisfaction will affect their technology adoptions.

End-User Satisfaction (EUS) may be one of the most-studied IS constructs. Various researchers have conducted a host of studies trying to understand the antecedents and consequences of EUS. DeLone and McLean (1992) reviewed relevant literature of IS success measures. They identified user satisfaction as one of six important IS success measurements. In their model of IS success, user satisfaction interacted with systems use. Their study reviewed the development of user satisfaction measures with a focus on using it as an information systems success indicator. They found 33 studies that used user satisfaction as a measure of IS success.

Various researchers have developed different measurements for user satisfaction. For example, Bailey and Pearson (1983) presented a 39-item instrument for measuring user satisfaction. Doll and Torkzadeh (1988) also provided a 12-item instrument measuring user satisfaction focusing on content, accuracy, format, ease of use, and timeliness. Numerous researchers have adopted their instruments for measuring user satisfaction.

However, some studies have suggested that end-user satisfaction measures are not cohesive. Bokhari (2005) in his meta-analysis identified three categories of user satisfaction measures: user attitudes towards an information system, user satisfaction in terms of information quality, and perceived IS effectiveness. Some researchers used a similar construct of customer satisfaction in studying mobile-computing satisfaction. In the marketing literature, a dominant paradigm in customer satisfaction and dissatisfaction is the expectancy disconfirmation paradigm (Anderson, 1973). The idea is that customer satisfaction is a relative measure between people's expectation and their perceived performance of a product. The perceived product performance can be above, at, or below people's expectation about the product. Therefore, the positive disconfirmation and negative disconfirmation of these expectations can lead to customer satisfaction and dissatisfaction (Perkins, 2012).

In the current study, the conceptual model focuses on the effects of an employee's mobile-computing satisfaction. This study extends user satisfaction into the mobile computing context. As introduced in Chapter I, mobile-computing satisfaction concerns an employee's perceptions about how satisfied they are regarding their mobile-computing needs. Mobile computing devices that have higher IPSI scores lead to higher mobile-computing satisfaction, which in turn leads to higher mobile-computing-device-adoption intentions at workplaces. Therefore, mobile-computing satisfaction is the first mediator in the conceptual model.

4.2. Mobile-computing dissatisfaction

In this study, mobile-computing dissatisfaction is another important mediator that affects an employee's mobile-computing-device-adoption intention at workplaces. As discussed in the literature, dissatisfaction acts independently of satisfaction. For example, people who have low satisfaction do not necessarily have high dissatisfaction. In the past, most researchers viewed mobile computing devices as consumer products. They used consumer satisfaction and dissatisfaction measures to study people's post-purchase behaviors or mobile IT service purchases (Turel, et al., 2006).

The disconfirmation paradigm in consumer satisfaction and dissatisfaction from marketing literature provided some foundation for the user dissatisfaction construct in the conceptual model in the current study. Chow and Zhang (2008) studied how to identify satisfiers and dissatisfiers using consumer satisfaction and dissatisfaction intensities. By referring to Herzberg's two-factor theory (Herzberg, 1968), their study identified satisfaction and dissatisfaction are two independent factors.

In the MIS discipline, researchers have incorporated the user dissatisfaction construct less frequently. User dissatisfaction is sometimes replaced with user complaints with information systems or appears together with the user satisfaction factor. For example, Shirani, et al. (1994) used the confirmation/disconfirmation of user expectations to explore user information satisfaction in their model of user information satisfaction. They suggested a favorable positive disconfirmation yields higher satisfaction while an unfavorable negative disconfirmation yields higher dissatisfaction.

Studies about user resistance to information systems implementation also provided some additional insights about the user dissatisfaction measure. User resistance is the user's adverse attitude or behavior toward new information systems changes. Both user resistance and user dissatisfaction concepts involve adverse attitudes toward new information systems. Klaus and Blanton (2010) proposed 12 determinants that affect user resistance to enterprise system implementations using the psychological contract concept. They categorized these determinants into four key areas: individual, system, organizational, and process issues. Their study suggested that the perceived unmet promise in these areas leads to user resistance behavior. Following the psychological contract concept, Klaus (2011) studied how perceived justice affects users' attitudes toward IT-enabled change in organizations. Both studies analyzed information systems at the organization level. Nonetheless, the concept of unmet promises is similar to the disconfirmed expectancy paradigm. User dissatisfaction leads to user resistance as well.

In this dissertation, an employee's mobile-computing dissatisfaction negatively affects his/her mobile-computing-device-adoption intention. Mobile computing devices that have low IPSI score are perceived as being unable to support the employee's information-processing activities at workplaces very well. Therefore, lower IPSI score leads to higher mobile-computing dissatisfaction, which in turn leads to lower device adoption intentions at workplaces. The mobile-computing dissatisfaction construct in the current study is another important mediator between the IPSI and an employee's mobile-computing-device-adoption intention. Chapter III develops instruments for both mobile-computing satisfaction and dissatisfaction constructs.

In previous literature, when researchers studied technology adoption, a dominant theoretical framework is the Technology Acceptance Model (TAM) developed by Davis (1989). The next section reviews TAM and identifies the connections between TAM and the IPSI framework in this study.

5. Technology Acceptance Model

Davis (1989) in the original TAM predicts people's technology adoption using two constructs: perceived usefulness (PU) and perceived ease of use (PEU). Based on the Theory of Reasoned Action (TRA) by Ajzen and Fishbein (1980), TAM is a dominant model when studying technology adoptions. Researchers in the MIS discipline have extensively tested and validated TAM and its variants in different studies (Venkatesh, et al., 2012).

TAM is a simple, powerful model in explaining users' technology adoption behavior. However, as suggested by Gebauer (2008), neither TAM nor TTF are very specific regarding the antecedents of PU or PEU. When examining task-related technology adoptions, TTF often provides better results.

TAM is very useful in explaining the technology adoptions behavior once the PU and PEU is measured (typically about mature technologies), but not so useful in predicting the factors that affect the perceptions about usefulness and ease of use. Therefore, the model itself provides limited information about how, in practice, people adopt new technologies at workplaces. For example, according to TAM, if employees perceive the mobile computing technology is useful and easy to use, they are more likely to adopt it. However, factors that determine the PU and PEU constructs in TAM are missing. The "catch-all" and abstract nature of TAM makes it difficult to capture the more practical drivers of technology adoption decisions in organizations.

In this study, the IPSI framework focuses on developing a more practical and tangible measure of how well mobile computing devices support an employee's information-processing activities. Therefore, the IPSI is able to identify factors that drive an employee's perceptions about usefulness and ease of use in the context of mobile-computing-device adoption decisions.

Venkatesh, et al. (2003) extended the original TAM and named it as the Unified Theory of Adoption and Use of Technology (UTAUT). In UTAUT, four key constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) were direct determinants of usage intention and behavior. That model also proposed that gender, age, experience, and voluntariness of use moderate the impact of the four key constructs on usage intention and behavior. The social influence construct of UTAUT provided some insights about other important factors that affect an employee's mobile device adoption intention at workplaces.

6. Social Influence

In Social Cognitive Theory (SCT) (Bandura, 1988), people learn to adopt technology by observing what others do. Therefore, subjective norms, organizational culture, and peer pressure all influence an employee's potential mobile-computing-device-adoption intentions. Consequently, to better explain an employee's mobile-computing-device-adoption intentions at workplaces, social influence is identified as another important construct in this dissertation's conceptual model.

6.1. Unified Theory of Adoption and Use of Technology

Venkatesh, et al. (2003) defined the social influence construct in UTAUT as the degree to which an individual perceives that other important people believe he or she should use the new system (p. 451). After comparing existing theories, they have identified three dimensions: subjective norm, social factor, and image.

They adopted the definition of subjective norm from the Theory of Reasoned Action (Ajzen 1991; Davis et al., 1989) as a person's perception that most people who are important to him/her think he/she should or should not perform the behavior in question (p.452). The definition of social factor adopted from Thompson, et al. (1991) is the individual's internalization of the reference group's subjective culture and specific interpersonal agreements that the individual has made with others, in specific social situations (p.452). The definition of image adopted from Moore and Benbasat (1996) is the degree to which use of an innovation is perceived to enhance one's status in one's social system (p.452).

In this study, mobile computing devices have some unique characteristics that distinguish them from other information systems. Using such devices can convey personal information to others. For example, if supervisors use certain types of mobile computing devices at work, their subordinates may perceive that behavior as either an encouragement or a discouragement of similar device usage, depending on the subculture in that department. In another example, an employee may want to use the same mobile devices as his/her coworkers, just to conform to the subjective norm of the group. Therefore, perceived norms about using these devices at workplaces and perceived social status associated with these devices have important impacts on an employee's adoption intention.

Another unique characteristic of mobile computing devices is their high mobility and visibility. The mobility of these devices enables employees to access and reply to important information at any time. Visibility enables employees to convey nonverbal communication such as personal preferences, styles, and tastes to others. Therefore, these devices have another important function: helping employees with their impression management efforts.

6.2. Impression Management

Schlenker (1980) defined impression management as behaviors people exhibit to create and maintain desired impressions on others. Previous studies in impression management focused on verbal or face-to-face interactions. For example, Gardner and Martinko (1988) examined impression management behaviors in organizations. They stated that self-presentation was the most prominent means of managing impressions and explored verbal self-presentation and the influence of these self-presentations.

Several studies in impression management have offered some evidence that employees use their mobile computing devices in their impression management efforts. For example, Scheibe, et al. (2009) studied how the different arrangements of office furniture affect people's impression. They also discussed how technology could act as an impression management tool in the office setting. As mentioned above, mobile computing devices have high visibility, which can help them to portray their desired impressions.

Another example of using mobile computing devices to manage impressions is the usage of mobile email services. In the modern business environment, the demand for email communication is rising rapidly. The omnipresence provided by mobile computing devices enables employees to stay connected with others all the time. However, different mobile computing devices have different capabilities for generating and viewing content. For example, smartphones have limited text-editing capabilities due to their small size. Tablets are larger than smartphones, but still provide limited capabilities for editing email messages. Laptop computers are most capable of editing email messages, but their mobility is lower than the other two devices.

Therefore, when an employee needs to respond to an email message from someone with whom he/she wants to maintain a good impression, he/she might find that a smartphone or a tablet cannot fulfill that need. On the other hand, if an employee travels very often and needs to respond to email messages in a quick, concise fashion, he/she needs to find a smartphone or a tablet that meets his/her requirements. For example, college professors can easily use smartphones or tablet computers to respond to students' office appointment requests. However, they will find it difficult to use such devices to respond to students' questions that require them to type long, detailed explanations in the message. These different impression management needs lead to different mobile device adoptions. As a result, mobile computing devices' capability to perform impression management tasks is another important dimension in the social influence construct.

As discussed above, this study defines the social influence construct as the social influence mobile computing devices have at workplaces. It includes three dimensions: perceived norms about using mobile computing devices at workplaces, perceived social status represented by mobile computing devices, and perceived device capabilities in performing impression-management-related tasks. Chapter III develops measurements for the social influence construct in the measurement model.

When studying mobile device adoptions, employees' self-judgments about how well they can handle these devices also affect their adoption intentions at workplaces. The next section reviews literature about Mobile Computing Self-Efficacy (MCSE).

7. Mobile Computing Self-Efficacy

People's knowledge about various information systems grows as technology advances. One of the key characteristics about today's workforce is that younger people are more comfortable with new technologies than older generations (Messer, 2012). When studying employees' mobile device adoptions, one of the important factors affecting employees' adoption intentions at workplaces is their level of mastery of these devices.

In Social Cognitive Theory (SCT), self-efficacy is a person's belief in his/her capability to perform a specific task (Bandura, 1977). Researchers in the MIS discipline have adopted and validated SCT in studying technology adoptions.

Using SCT, Compeau and Higgins (1995) defined computer self-efficacy (CSE) as “an individual judgment of one's capability to use a computer” (p. 192). In their study, the performance outcome expectancy, personal outcome expectancy, self-efficacy, affect, and anxiety influenced an individual’s technology usage behavior. Researchers suggested that CSE plays a significant role in an individual’s decision to use computers (Compeau, et al., 1999).

Marakas, et al. (1998) in their study about CSE reviewed the root, antecedents, and consequences of the CSE construct. They stated that CSE would affect people’s performance with computers and categorized CSE into general and specific CSE.

Discussions about CSE also apply to mobile computing devices. Some researchers have tried to define and test the MCSE construct. For example, Wang and Wang (2008) developed a 45-item scale to measure that construct. Their study focused on five dimensions: basic mobile computer operations, the Internet, e-mail, specific mobile services, and mobile computer knowledge. However, their study focused on the narrow usage of email and the Internet of these devices. In addition, their scale is too lengthy for practical use in the current study.

In this study, an employee’s mobile computing self-efficacy positively influences his/her adoption intentions. Based on the relevant literature, the definition of MCSE is an employee’s judgment about his/her capability to use a mobile computing device at workplaces. Chapter III develops the measurement for MCSE.

8. Chapter Summary

This chapter provided a detailed review of relevant literature and developed the IPSI framework. It identified five major constructs in the new conceptual model: IPSI, mobile-computing satisfaction, mobile-computing dissatisfaction, social influence, and MCSE. Mobile-computing satisfaction and dissatisfaction mediate the positive relationship between IPSI and an employee’s mobile-computing-device-adoption intentions at workplaces. Chapter III operationalizes the conceptual model, develops survey instruments for the constructs, and discusses methodology issues.

CHAPTER III

METHODOLOGY

1. Chapter Overview

This chapter discusses the operationalization of the conceptual model and research methodology issues. Based on the literature discussed in Chapter II, this chapter presents the development of the measurement model, operationalizes constructs, and derives hypotheses.

First, this chapter develops survey instruments for the new construct: the Information-Processing Support Index (IPSI). By following relevant literature about scale development, this study generates, validates, and refines scale items measuring the IPSI components. The discussion about relevant literature and the IPSI framework leads to the development of candidate items list for refinement. These items are then validated through an instrument refinement process and two pilot studies.

The next section discusses the operationalization of other constructs in the conceptual model through adopting well-developed measurement scales from previous literature. These survey instrument items are refined and modified to fit the current study context.

Based on relevant literature, this chapter derives hypotheses among these constructs in the measurement model. Finally, this chapter discusses methodology issues related to ensuring the convergent validity, discriminant validity, and reliability of the final survey instrument.

2. Conceptual Model Development

Chapter II reviewed relevant literature and identified the need to study mobile-computing-device adoption in organizations at an individual level from the information processing perspective. To answer the research question about why and how people adopt mobile computing devices at workplaces, this study identifies five major constructs in the conceptual model: the IPSI, mobile-computing satisfaction and dissatisfaction, social influence, and MCSE.

As introduced in Chapter II, this study uses the IPSI framework to measure how well mobile computing devices support an employee's information processing activities. Two major components in the IPSI framework are the Content Generation Score (CGS) and Content Consumption Score (CCS). They are used to capture the perceived support of mobile devices for the two major types of information processing activities. A higher score in the IPSI indicates that a mobile computing device supports an employee's information processing activities better. In the conceptual model, it leads to higher mobile-computing-device-adoption intention at workplaces.

On the other hand, a higher IPSI score also indicates a mobile computing device fits an employee's information-processing tasks better. As predicted by the Task Technology Fit (TTF) theory (Goodhue and Thompson, 1995), a better fit between a mobile computing device (technology) and an employee's tasks increases the employee's mobile-computing satisfaction while it decreases his/her mobile-computing dissatisfaction. Literature about user satisfaction indicates that mobile-computing satisfaction and dissatisfaction are two independent factors (Anderson, 1973; Doll and Torkzadeh, 1991; Hertzberg, 1965). As proposed in the conceptual model, mobile-computing satisfaction and dissatisfaction mediate the positive relationship between IPSI and an employee's mobile-computing-device-adoption intention.

Studies in innovation diffusion, impression management, and cognitive science have suggested that social influence and Mobile-Computer-Self-Efficacy (MCSE) are two constructs that also affect an employee's mobile-computing-device-adoption intention. As discussed in Chapter II, social influence (including subjective norms of mobile device use, social status associated with these devices, and device capabilities about impression management) and MCSE positively influence an employee's mobile-computing-device-adoption intention. Figure 3-1 below demonstrates the conceptual model developed in this study.

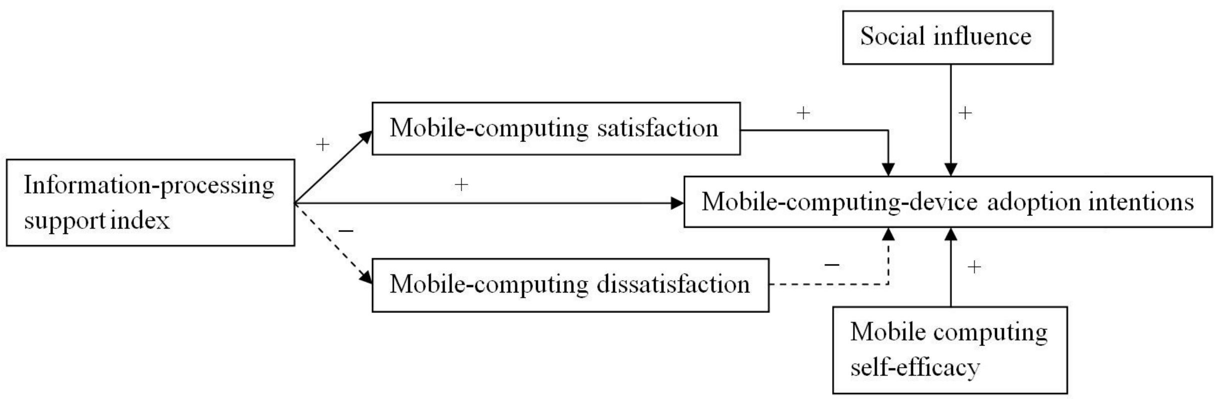


Figure 3-1. Mobile-computing-device-adoption intention model

3. Model Operationalization

The following sections operationalize constructs in the conceptual model. First, this study develops a new multi-item scale to measure the Information-Processing Support Index. As suggested by various researchers, to ensure the validity and reliability of scales it is important to select the initial scale items carefully at the very beginning of scale development (Nunnally, 1978). Therefore, issues in each step of the IPSI scale development (e.g., conceptual definitions, initial item generation, convergent validity, discriminant validity, and reliability) are discussed in the following section.

3.1. Information-Processing Support Index

Previous literature used the information processing view of firms to understand why organizations have different structures and communication channels (Galbraith, 1974). Information systems can help firms' performance at an organization level by eliminating the need to process information or increase the capability to process information (Daft and Lengel, 1986). On the other hand, studies about technology adoptions such as the Technology Acceptance Model (TAM) (Davis, 1989) and Task-Technology Fit (TTF) theory (Goodhue and Thompson, 1995) have focused on organization level technology adoptions in more mature technologies (Gebauer, 2008). The perceived usefulness, perceived ease of use, and the fit between task and technology are strong predictors about people's technology adoptions behaviors. However, there is a lack of research on identifying what are the antecedents of these predictors, and how people develop their technology adoption intentions.

The current study tries to fill this gap by adopting the information processing view at the individual level to explain employees' mobile-computing-device-adoption intentions at workplaces. By examining how employees process information in workplaces, the IPSI score indicates how well mobile computing devices support employees' information-processing activities. The IPSI uses the CGS and CCS to measure the two types of information-processing activities employees perform. This study defines the IPSI as an indicator of the level of information processing support mobile devices provide for employees.

As suggested by Churchill (1979), scale development includes steps of specifying the domain of construct, generating a sample of items, collecting data for the pilot study, purifying measurements, collecting data for the primary study, assessing reliability and validity, and developing norms. This study follows these steps to develop the IPSI scale.

Domain specification and survey item generation

Few studies have examined technology adoption at workplaces from the information-processing perspective. From the information processing view, employees are information-processing nodes inside the organizational networks. Each of these employees/nodes has two major streams of information/content flows: information/content inflow and outflow. Therefore, from an individual employees' perspective, content generation refers to the information/content outflow while content consumption refers to the information/content inflow.

In order to measure the CGS and CCS, this study develops survey items asking employees about their perceptions of 1) the capabilities of a mobile device in performing content generation/consumption activities, and 2) the degree to which their jobs require them to perform these two activities.

The Morgan Stanley study (2011) used content creation and consumption to distinguish these two information-processing activities. Although focused primarily on consumer usage of tablet computers, their study revealed several work-related activities in the content creation category (communication, and general/specific work-related content creations) and the content consumption category (general web browsing, and communication-related content consumptions). According to their findings, consumers use their PCs and tablet computers mainly for content-consumption activities. However, most of the work-related tasks are in the content generation category. People use their mobile computing devices differently at workplaces than at home. In order to supplement the need to use their devices for work, employees use various accessories such as Bluetooth keyboards, stylus pens, etc. to increase the device's capabilities in performing work-related tasks. Based on the discussion above, the current study generates a list of content-generation/consumption activities people perform at workplaces and uses that list to assess device capabilities and job requirements in terms of content generation and consumption.

Generally, this study proposes that there are two major categories of people's information processing activities at workplaces: communication-related and work-related activities. In Morgan Stanley's study (2011), they included general and specific work-related content creations. Using the specific content creation/consumption activity to understand people's usage of mobile devices at workplaces may be useful. However, since people's jobs vary greatly, it is hard to create a generalizable measurement using a specific content creation/consumption activity. As a result, this study uses more general work-related content generation and consumption activities to achieve the most generalizablity in the resulting instrument.

Table 3-1 below shows the list of content-generation and consumption activities used in this study to develop candidate items for measuring the CGS and CCS.

Activities at job	Content generation	Content consumption
Communication activities	Creating email messages, and IM/social network messages	Reading email messages, and IM/social network messages
Work-related activities	Creating work-related documents, editing work-related documents	Gathering information from the Internet, reviewing work-related documents
Networking activities	Creating content on social network and other web pages	Reading content on social network and other web pages

Table 3-1. Content generation and consumption activities at workplaces

By using seven-point Likert-type scales anchored at 1: strongly disagree and 7: strongly agree, this study generates five candidate items for each component in the IPSI framework. For the CGS, proposed survey items measure the perceived device capabilities to perform content generation activities, and the perceived job requirements about content generation activities. For the CCS, the survey items measure perceived device capabilities in performing content consumption activities, and the perceived job requirements about content consumption activities.

As indicated in Figure 3-2, the IPSI framework uses aggregated device-related and job-related measurements in calculating CGS and CCS. The CGS_{Device}, CGS_{Job}, CCS_{Device}, and CGS_{Job} are all aggregated scores from survey items. A higher CGS_{Device}/CGS_{Device} score indicates a device has better capabilities in performing content generation/consumption-related tasks, a higher CGS_{Job} score indicates a job requires more content generation/consumption activities.

Therefore, by comparing the paired CGS and CCS sub scores on device capabilities and job requirements, the CGS and CCS captures how well mobile devices support job-required content-generation/consumption activities respectively. If a device has scores that match or exceed a job's scores, the device is able to support the job-required content generation and/or consumption activities. Otherwise, the device is not able to support all the job-required content generation and/or consumption activities.

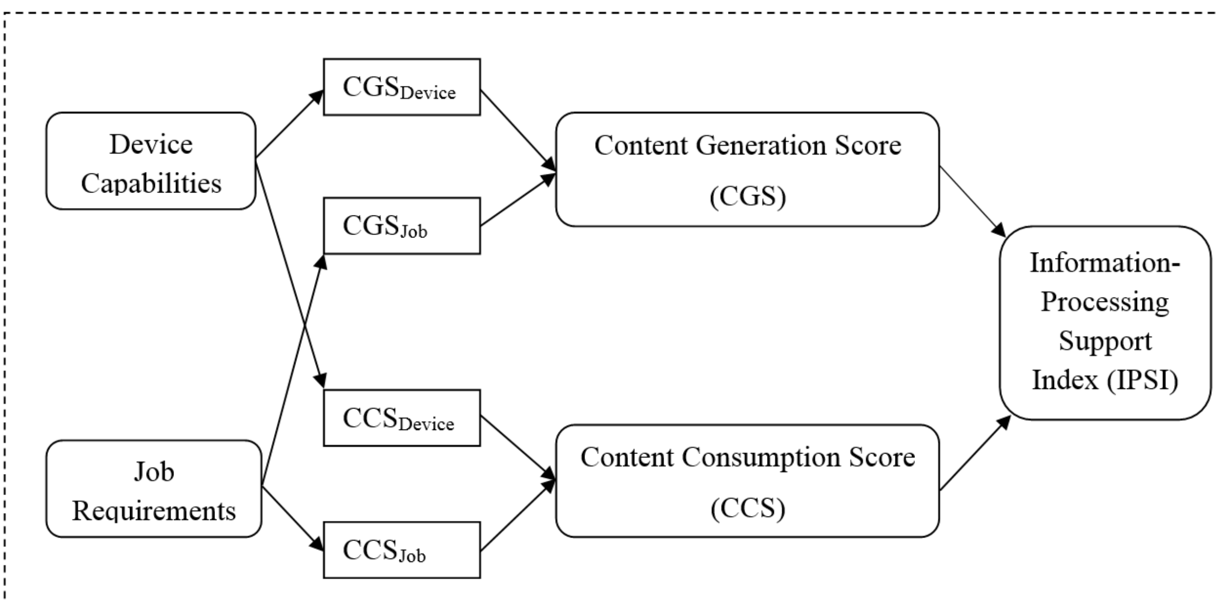


Figure 3-2. Information-Processing Support Index (IPSI) framework

The IPSI framework uses the following equations to calculate CGS, CCS, and IPSI scores:

Equation (1): $CGS' = 1 - \frac{CGS_{Job} - CGS_{Device}}{MAX(CGS_{Job} - CGS_{Device})}$

$$\text{CGS}=\begin{cases} CGS & if\ CGS' \geq 1 \\ CGS'^2 & if\ CGS' < 1 \end{cases}$$

Equation (2): $CCS' = 1 - \frac{CCS_{Job} - CCS_{Device}}{MAX(CCS_{Job} - CCS_{Device})}$

$$\text{CGS}=\begin{cases} CCS' & if\ CCS' \geq 1 \\ CCS'^2 & if\ CCS' < 1 \end{cases}$$

Equation (3): $IPSI = CGS \times W_{cgs} + CCS \times W_{ccs}$

In Equation 1 and 2, the CGS' and CCS' scores were computed as the differences between device-related and job-related sub scores scaled by their maximum differences. The resulting scores are ranging from zero to two, in which a score of one indicates the neutral point (the device-related scores equal the job-related scores) and a higher score means better perceived device support. The CGS' and CCS' are the raw scores. As suggested by the prospect theory (Kahneman and Tversky, 1979), when evaluating the value of choices, people discount the losses more than they value the gains. Therefore, when the perceived device capability falls below the perceived job requirements, the perceived support of mobile device will decrease faster. To reflect these effects, when calculating the CGS and CCS, the IPSI framework penalizes the raw scores CGS' and CCS' less than one by squaring them, reflecting the effect that losses loom larger than gains.

In order to account for the possibility that different jobs focus on content generation and/or consumption activities differently, the IPSI framework also uses a weight function. In the survey instrument, employees rate the relevant importance of content generation/consumption activities in their jobs on a 1-to-7 scale anchored at 1: extremely unimportant and 7: extremely important. In that way, the more important aspect of information processing activities is assigned with a higher weight in the final calculation of the IPSI score. Equation 3 shows how to calculate the IPSI score with the W_{cgs} and W_{ccs} functions.

Instrument refinement

Instrument refinement is conducted to assess the semantic content of generated items. The refining process establishes the content validity of survey items in the instrument. After generating the candidate items for the survey instrument, this study will refine/examine these items by asking a group of undergraduate students to perform the Q-sort test (Straub, Boudreau, and Gefen, 2004). The Q-sort test asks the students to perform two tasks: one, to rank items in each construct (CGS_{Device}, CGS_{Job}, CCS_{Device}, and CGS_{Job}) in terms of their relevancy to the underlying concepts of content generation and consumption; and two, categorize all items into the two underlying categories (constructs). If the Q-sort test results converge with the conceptual definitions of these constructs, the candidate survey instruments list has demonstrated its content validity. After refining the items in the candidate list, a pilot study follows to assess the reliability and validity of the survey instrument.

In the following sections, this study defines and operationalizes the rest of the constructs in the conceptual model through adopting well-developed instruments. Therefore, the content validity issue is resolved by carefully reviewing relevant literature. After the operationalization of all constructs in the conceptual model, this chapter discusses methodology and data analysis issues in the pilot and main study.

3.2. Mobile-Computing Satisfaction

Various researchers have studied user satisfaction. Doll and Torkzadeh (1988) defined end-user satisfaction as the end user's positive attitude toward the information system they are using. Similarly, in DeLone and McLean's (1992) model of information system success, they listed 33 studies about user satisfaction used either single overall satisfaction ratings or multi-attribute satisfaction measures.

Based on the relevant literature, this study defines an employee's mobile-computing satisfaction as his/her opinion regarding whether he/she is satisfied with his/her mobile-computing needs at work. As suggested by the various studies about user satisfaction measurements (Bokhari, 2005; Doll and Torkzadeh, 1988), this study proposes measuring this construct from the employees' overall satisfaction about mobile computing needs, satisfaction about organizational support in mobile computing device usage, and satisfaction about mobile device performance in job requirements. By focusing on mobile-device-related measures, the mobile-computing satisfaction instrument can provide measurements that are more relevant in the context. The survey items measuring this construct are presented in Appendix A.

3.3. Mobile-Computing Dissatisfaction

Mobile-computing dissatisfaction is identified as another mediator between the IPSI and employees' mobile-computing-device-adoption intentions. According to the disconfirmed expectancy paradigm in the Marketing literature, when the actual system performance differs from the user's expectation, a positive disconfirmation yields higher satisfaction while a negative disconfirmation yields higher dissatisfaction. In the MIS filed, user dissatisfaction is related to information systems resistance, which is the adverse attitude a user has toward new information system implementation. Klaus and Blanton (2010) found four categories of factors determine a user's resistance using the psychological contract concept: individual, system, organizational, and process issues.

Based on the discussions above and relevant literature, this study defines an employee's mobile-computing dissatisfaction as an employee's adverse opinion regarding his/her mobile-computing needs at work. By following the disconfirmed expectancy paradigm and literature in user resistance, this study focuses on a user's perception about unmet expectations about their mobile computing needs, the lack of organizational support, and unmet device performance expectations. Those measures cover the areas of determinants of user resistance and dissatisfaction in organizations as identified in previous literature.

3.4. Social Influence

The social environment also influences employees' mobile device adoption intentions. In the technology acceptance literature, Venkatesh, et al. (2003) defined social influence as employees' perceptions about how important others think whether they should use the new system. In social cognitive theory, people make their technology adoption decisions by observing what others do (Bandura, 1988). If the majority of people around an employee choose to use certain technology, that employee is more likely to adopt it. With the ever-increasing power of information and communication technology, social influence is another important factor affecting an employee's mobile-computing-device-adoption intention at workplaces. This study defines social influence as social factors and interactions that influence an employee's mobile-computing-device-adoption intentions.

The social influence construct contains three dimensions: subjective norms about mobile computing device usage at workplaces, social status associated with the usage of mobile computing devices, and impression management capabilities of these devices. The subjective norms and social status will determine whether an employee perceives using a mobile device is accepted by the social group or is appropriate to the desired social class norms. Impression management capability, on the other hand, determines how well the mobile computing device can be used to enhance an employee's impression upon others, and to influence others.

These dimensions capture the social interactions and influences that are occurring at workplaces. This study adopts survey items from relevant literature to measure these dimensions. For the impression management dimension, most of the literature focuses on impression management behaviors such as face-to-face interactions and other verbal behaviors (Wayne and Ferris, 1990). This study uses an item in the survey instrument to indicate the employee's perception about how well mobile computing devices support their impression management activities.

3.5. Mobile Computing Self-Efficacy

As discussed in social cognitive theory, self-efficacy is a person's belief in his/her capability to perform a specific task (Bandura, 1977). Based on that, Compeau and Higgins (1995) defined computer self-efficacy (CSE) as "an individual judgment of one's capability to use computer" (p. 192). Researchers generally agree that higher CSE leads to higher productivity using computers. Marakas, et al. (1998) reviewed the development in the CSE construct and categorized it into general and specific CSE. Recently, Wang and Wang (2008) developed a 45-item Mobile Computing Self-Efficacy (MCSE) instrument that included five dimensions with both general and specific MCSE.

As discussed above, the current study defines MCSE as an individual judgment about one's capability to use mobile computing devices in work environments. This definition avoids overly detailed specification about how a person perceives his/her ability to perform specific tasks, and focuses on the general judgment people have regarding their mobile computing device usage capabilities. By adopting part of the MCSE instruments (Wang and Wang, 2008), this study proposes a set of instruments measuring the MCSE construct from the general knowledge about mobile computing devices, mobile applications, information gathering, and problem solving. Therefore, the MCSE instrument in this study focuses on the general MCSE.

3.6. Mobile-computing-device-Adoption Intentions

Finally, this study adopts survey instruments from the technology acceptance literature to measure an employee's mobile-device-adoption intention at workplaces. These instruments were well developed and adopted in the literature. Table 3-2 summarizes the model operationalization.

Constructs in the model	Conceptual Definition	Operational Definition	References
Mobile computing device characteristics	CGS_{Device}, CCS_{Device}	Aggregated score from survey items about perceived mobile computing device's capabilities related to content consumption and generation.	Developed in this study.
Job requirement characteristics	CGS_{Job}, CCS_{Job}	Aggregated score from survey items about content generation and consumption related job requirements.	Developed in this study.
CGS and CCS	Scores indicate how well mobile computing devices support content generation and consumption activities.	$CGS' = 1 - \frac{CGS_{Job} - CGS_{Device}}{MAX(CGS_{Job} - CGS_{Device})}$ $CCS' = 1 - \frac{CCS_{Job} - CCS_{Device}}{MAX(CCS_{Job} - CCS_{Device})}$	Developed in this study.
Information-Processing Support Index (IPSI)	An index score indicates how well mobile computing devices support employees' information-processing activities.	$IPSI = CGS \times W_{cgs} + CCS \times W_{ccs}$ W_{cgs} and W_{ccs} are the relative importance of job-required content generation and consumption activities indicated by respondents.	Developed in this study.

Constructs in the model	Conceptual Definition	Operational Definition	References
Mobile-Computing Satisfaction	An employee's opinion regarding whether he/she is satisfied with his/her mobile-computing needs at work.	Survey items indicate whether an employee is satisfied about his/her mobile computing need.	Doll and Torkzadeh, (1988); DeLone and McLean (1992, 2003).
Mobile-Computing Dissatisfaction	The opinion a person has regarding to whether he/she is dissatisfied with the mobile computing devices at work.	Survey items indicate whether an employee is dissatisfied about his/her mobile computing need.	Anderson (1973); Klaus and Blanton, (2010).
Social Influence	Social factors and interactions that influence an employee's mobile-computing-device-adoption intentions	Survey items indicate the perceived norms of using mobile devices, status associated with these devices, and perceived device capabilities in performing impression-management-related tasks.	Thompson et al. (1991); Moore and Benbasat, (1991); Wayne and Ferris, (1990).
Mobile Computing Self-Efficacy (MCSE)	An individual judgment of one's capability to use mobile computing devices.	Survey items adopted from previous research that indicates a person's belief about his/her capability to use mobile computing devices.	Bandura (1986); Marakas, et al., (1998); Wang and Wang, (2008).
Mobile-computing-device-adoption intention	The extent to which an individual intends to adopt mobile computing devices for work.	Survey items adopted from previous research about technology adoptions in organizations.	Ajzen, (1991); Venkatesh, (2000)

Table 3-2. Summary of construct operationalizations

4. Hypotheses

According to the literature review in Chapter II and discussions above, this study derives the following hypotheses in the measurement model:

H1: The IPSI has a positive association with an employee's mobile computing device adoption intention.

H2: Mobile-computing satisfaction mediates the positive relationship between the IPSI and an employee's mobile computing device adoption intention.

H3: Mobile-computing dissatisfaction mediates the positive relationship between IPSI and an employee's mobile computing device adoption intention.

H4: Social influence of mobile computing devices has a positive association with an employee's mobile computing device adoption intention.

H5: An employee's Mobile Computing Self-Efficacy (MCSE) has a positive association with his/her mobile computing device adoption intention.

5. The Mobile-Computing-Devices-Adoption Intention Model

Figure 3-3 below shows the measurement model with hypotheses derived from literature.

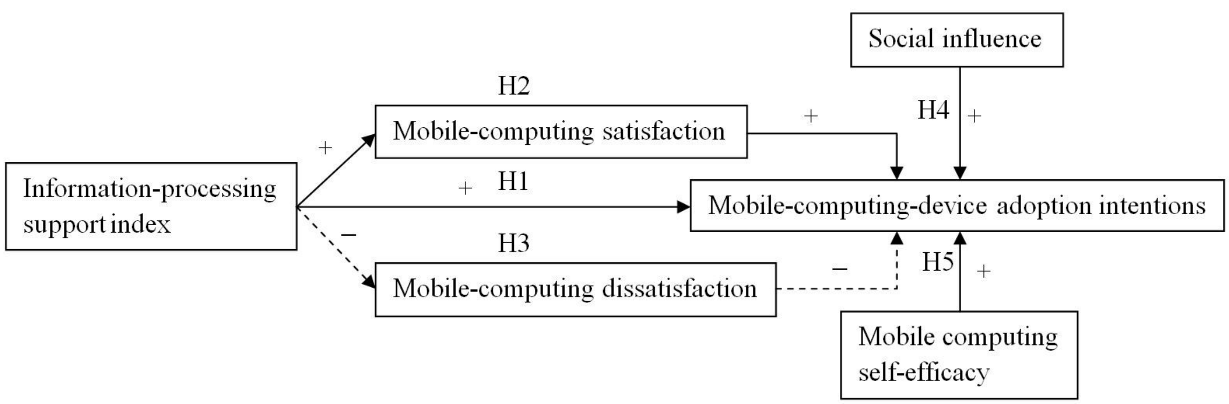


Figure 3-3. The measurement model with hypotheses

(Solid line indicates positive relationship and dashed line indicates inverse relationship)

6. Methodology and Data Analysis

All survey items generated in this study need to be tested for the convergent validity, discriminant validity, and reliability before conducting the main data collection.

6.1. Validity issues

The current study develops a new multi-item instrument for the IPSI following the domain-sampling model, which assumes that each variable has a domain of content corresponding to it (Nunnally and Bernstein, 1994). By following the steps of domain specification, and measurement refinement, the survey instrument possesses content validity. Content validity ensures an instrument is truly measuring the underlying concept. The proposed Q-sort test also provides empirical support for the content validity of the instrument.

When the survey instrument items are generated and refined, they are ready for a pilot study. The pilot study serves as a check for the convergent validity, discriminant validity, and reliability issues in the instrument. There are several techniques that can help ensure those issues are not harming the hypotheses testing for the measurement model.

A Confirmatory Factor Analysis (CFA) is conducted to assess the convergent validity, which is the degree to which the measurements correlate with each other when measuring the same concept; and the discriminant validity, which is the degree to which measurements differ from each other when measuring different concepts. The CFA technique form factors based on the items' correlation. Items identified within the same factor correlate to each other higher than items that are not in that factor. Therefore, by examining the factor loading results from a CFA, high convergent validity requires items measuring the same constructs load on one factor. On the other hand, high discriminant validity requires items measuring different constructs load into different factors. Items fail to load properly or are cross-loaded on more than one factors need to be modified or dropped from the final instrument list.

6.2. Reliability issues

The reliability of the survey instrument refers to "the degree to which measures are free from error and therefore yield consistent results" (Peter, 1979 p. 6). One commonly used measure of reliability is the internal consistency measure (e.g., Cronbach's alpha) (Jarvis, Mackenzie, & Podsakoff, 2003). In the data analysis of this study, Cronbach's alpha will be calculated to assess the reliability of all survey items. To demonstrate acceptable level of reliability in the multi-item instrument, the alpha coefficients should exceed 0.7.

6.3. Hypotheses testing

The pilot study validates and refines the survey instruments for the main study. In the main study, the revised survey instruments are used to gather empirical data for the hypotheses testing purposes. Chapter IV will discuss the hypotheses testing in more detail. Multiple regressions and Structural Equation Modeling (SEM) techniques will be used to test the significance of each hypothesis and the paths in the structural model. In addition, a power analysis is performed to determine the optimal sample size for the main study in order to ensure the proposed hypotheses testing possesses adequate statistical power.

6.4. Common method biases

Since the primary data-collection method in this study is survey questionnaire, the data analysis must pay close attention to the potential biases introduced by the method. Common method biases refers to the method variance that is attributable to the measurement method rather than to the constructs of interest (Podsakoff, et al., 2003). The common method biases can potentially have a confounding effect in the hypotheses testing, which weakens the statistical conclusions of the data analysis. Several ways to control this bias are suggested including better-designed instruments, marker variable techniques, and temporal separations (Podsakoff, Mackenize, & Podsakoff, 2012). In this study, the survey instrument list is not very long, most of the items in the instrument do not involve a high level of mental effort to generate the answers, and the constructs are well defined. Therefore, the common method bias in the current study is not likely to create problems in the data analysis. In the next section, this chapter briefly introduces the pilot and main study.

7. Pilot and Main Study Introduction

7.1. Instrument refinement

Before the pilot study, the IPSI framework needs to be refined to ensure its content validity. As discussed earlier, business major undergraduate students in a southern public university will be recruited for the instrument refinement process for the IPSI construct.

The students will perform two tasks: ranking and categorizing. The ranking task lists survey items measuring the CGS and CCS. Students are asked to rank these item based on their relevancy to the concepts of content generation and consumption.

The categorizing task lists survey items measuring the CGS and CCS. Students are asked to categorize these items into two categories: content generation and consumption.

Each student was given only one task. The results showed how well each item reflects the underlying concepts. If the results converge, which means all items are ranked and categorized properly according to the concepts they represent, the generated items list has high content validity. If not, items that are not properly ranked/categorized will need to be revised or dropped from the final items list.

7.2. Pilot study

The pilot study recruited undergraduate students from the same university. The refined survey questionnaires were distributed to them. In order to provide relative responses in job-related measures, the survey instrument utilized a short description to set up the scenario for the participants. The students were required to think that their job is to get a college degree; their classmates and professors are coworkers and supervisors; their daily classroom activities and assignments are job-required activities, and they are using mobile computing devices for these activities. By setting up this scenario, the pilot study can show weaknesses in the design of survey and potential issues with data collections.

Their responses are coded and prepared for the assessment of convergent validity, discriminant validity, and reliability of the survey instrument. The Cronbach's alpha and CFA are performed. Items that are having low coefficient alphas or low factor loadings in the CFA are revised or dropped from the final survey instrument.

7.3. Main Study

The main study provides empirical support for the hypotheses in the measurement model. This study will conduct its main data collection in one large public university in the central part of China. It has two purposes: validating the measurement model and providing initial results concerning the proposed relationships in the conceptual model.

In an attempt to manage employee-owned mobile devices at work, the Chinese university recently launched a program to provide its 1,800+ employees with smartphones. The program provides 14 types of smartphones, with operating systems ranging from iOS to Android to Windows Phone 7.5/8. In this program, all employees choose their own mobile computing devices (smartphones), and may use it for both personal and work-related purposes. These smartphones serve as the primary contact media through which the university notifies its employees about work-related issues. While employees cannot change the SIM cards in these smartphones, they can choose whether they want to use these devices at workplaces. This is a great opportunity to study how and why people choose different mobile computing devices at workplaces. Paper-based surveys questionnaires containing revised instruments are distributed to employees at the university.

8. Chapter Summary

This chapter discussed issues in conceptual model development, operationalization, instrument generation, and methodologies. First, this chapter discussed the development of the Information-Processing Support Index, specified the conceptual definitions, and generated a candidate list of survey items. Next, conceptual definitions and instruments about the mobile-computing satisfaction/dissatisfaction, social influence, and MCSE constructs were discussed. Third, this chapter discussed the hypotheses derived from the conceptual model and proposed methodologies to assess the validity and reliability issues associated with the survey instrument. Finally, this chapter provided an overview about the data collections in pilot and main study. Chapter IV discusses the instrument refinement process, pilot study, and data analyses results.

CHAPTER IV

DATA ANALYSIS

1. Chapter Overview

This chapter discusses the instrument refinement process for the Information-Processing Support Index (IPSI) and data analyses of the pilot and main study. First, candidate item list for the new measurement scale of IPSI was tested by a Q-sort test involving both categorizing and ranking tasks. The next section discusses the pilot study. Reliability, convergent validity, and discriminant validity of all measurement items were tested. Multiple regression and mediation analyses were conducted to test the hypotheses in the measurement model. Based on the results, the survey instruments were modified and the main study was conducted.

The last section discusses the main study's data analysis. Survey questionnaires containing modified instruments were translated into Chinese via a double translation process and distributed to participants. The main study collected survey data to assess the reliability and validity of all measurement scales and utilized multiple regression, structural equation modeling technique, and bootstrap-based mediation analyses to test proposed hypotheses.

2. IPSI Instrument Refinement

As introduced in Chapter III, the initial survey instruments for the IPSI have five items measuring each of the following constructs: CGS_{Device}, CCS_{Device}, CGS_{Job}, and CCS_{Job}. By asking the respondents to indicate their perceptions about device capabilities and job requirements in terms of content generation/consumption, these items capture how mobile computing devices vary in their perceived capabilities to support job-required information-processing activities. The IPSI score is then calculated using these four constructs. Therefore, the reliability and validity of the survey items measuring these sub-scores are essential to the IPSI measure.

This study included an instrument refinement process to ensure the content validity, convergent validity, and discriminant validity of the IPSI instruments. Initially, there were five survey items per construct in the instrument list. To assess how well these items represent their underlying constructs, the instrument refinement process utilized a Q-sort technique. The technique, discussed by various researchers (Segars and Grover, 1998; Storey et al., 2000; Straub, et al., 2004), is useful in evaluating both content validity and construct validity. In general, participants were asked to group items according to their similarity in a Q-sort test. If items representing the same construct were grouped together, they demonstrate high levels of convergent validity. On the other hand, if items representing different constructs were grouped into different sets, they have high discriminant validities. Overall, if the items were grouped into their underlying constructs correctly, they have shown high levels of content validity.

Since the items measuring perceived device capabilities and job-required information-processing activities are similar in their wordings, only four items measuring content generation and four items measuring content consumption were included in the Q-sort test. The "overall" items were excluded since the wordings of these items reveal the underlying constructs.

The Q-sort test was conducted with 30 undergraduate students from a large southern public university in the U.S. Undergraduate students are appropriate participants to perform the Q-sort test because most of them are familiar with multiple types of mobile computing devices such as smartphones, tablet computers, and laptop computers. The students also have adopted these mobile devices in their study-related activities. However, they have limited professional employment experience. Therefore, they cannot entirely represent how employees view their job-required content generation/consumption activities without special instructions. Based on these factors, the Q-sort test only shows the participants the eight activities that are used to construct the survey items. By not revealing the actual survey items, the current study was able to avoid potential confusion among the student participants about work-related situations.

In the Q-sort test, the participants were randomly assigned with either a categorizing task or a ranking task. The categorizing task asks participants to categorize the eight activities in the candidate items list measuring content-generation and consumption scores into two categories: content-generation activities and content-consumption activities. The ranking task asks participants to rank the same set of activities according to their relevance to content-generation and consumption activities. No definitions of content generation and consumption were given in these tasks. Table 4-1 and 4-2 below show the results of the two tasks in the Q-sort test.

Items	Content-Generation (# of responses)	Content-Consumption (# of responses)
Creating email messages	12	3
Creating IM/Social network messages/posts	12	3
Creating work-related documents	12	3
Editing work-related documents	12	3
Reading email messages	4	11
Reading IM/social network messages/posts	6	9
Browsing web pages	6	9
Reading/reviewing work-related documents	6	9

Table 4-1. Categorizing task results

Content Generation Activities	Rank	Content Consumption Activities	Rank
Creating work-related documents	1	Reading email messages	1
Creating email messages	2	Browsing web pages	2
Creating IM/social network messages/posts	3	Reading/Reviewing work-related documents	3
Reading email messages	4	Creating email messages	4
Reading IM/social network messages/posts	5	**Reading IM/social network messages/posts**	5
Browsing web pages	6	Creating work-related documents	6
Reading/Reviewing work-related documents	7	**Editing work-related documents**	7
Editing work-related documents	8	Creating IM/social network messages/posts	8

Table 4-2. Ranking task results

Overall, these results showed that the proposed items had acceptable levels of content validity, convergent validity, and discriminant validity. In the categorizing task, most participants were able to group items representing content generation and consumption activities into appropriate corresponding categories. The ranking task results showed that although most of the items were ranked properly according to their underlying concepts, some of them needed revision. Figure 4-1 demonstrates how the rankings of these activities change across the two underlying concepts.

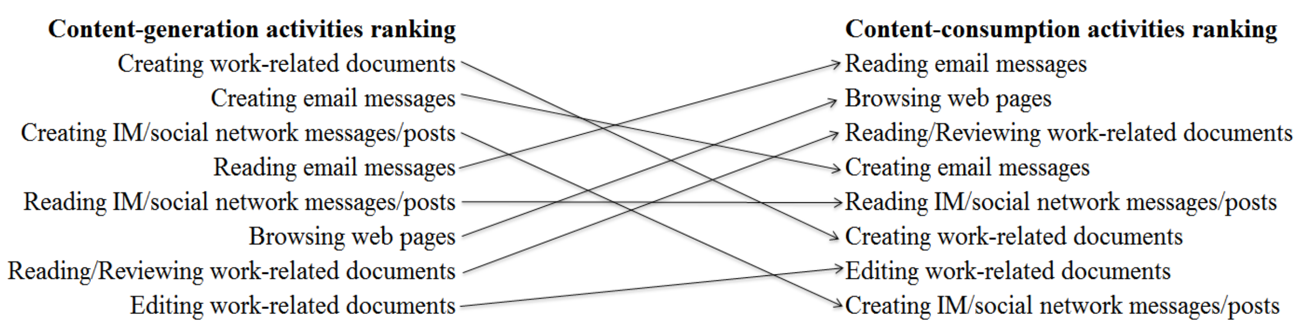


Figure 4-1. Ranking changes among items

As shown in Figure 4-1, most items representing the two concepts were ranked high in terms of their relevancy to their corresponding concepts. Therefore, these items demonstrated high levels of convergent validity and discriminant validity. However, among these items, "Editing work-related document" was ranked low in the content generation construct. Given that the students had very limited work experience, one possible explanation was that they could not relate this item to their own experience. In addition, since the survey item list already had "Creating work-related document", the participants may not be able to distinguish between editing and creating documents. As a result, the study combined these two items into "creating or editing work-related document".

Another potentially problematic item was "Reading IM/social network messages/posts". The rankings were the same across the two categories and were in the middle range. This item had some overlap with the items concerning email. It was possible that the students were confused between this item and other items such as reading email and browsing web pages. Therefore, the current study modified these items and combined items that were measuring similar aspects of job-required information processing activities.

The revised survey item list shown in Table 4-3 had four items per construct, measuring the overall content generation/consumption activities as well as specific activities that are related to communication (email and other messages), workflow (work related documents), and networking (social network and other web pages). A complete survey instrument for the IPSI and other constructs is presented in Appendix B.

Content Generation Items	Content Consumption Items
Creating or Editing email and other messages	Reading email and other messages
Creating or Editing work-related documents	Reading work-related documents
Creating or Editing content on social network and other web pages	Reading content on social network and other web pages
Overall content generation item	Overall content consumption item

Table 4-3. Revised CGS/CCS items list

The instrument refinement process found that the proposed instruments for the CGS and CCS components of the IPSI have acceptable levels of content validity, discriminant validity, and convergent validity. After revising the initial candidate item list, a pilot study was conducted.

3. Pilot Study

3.1. Introduction

The purposes of a pilot study are to assess reliability and validity issues in the instruments and to gather initial empirical support for the proposed hypotheses in the measurement model. As introduced in Chapter III, the current research conducted the main data collection in China. Therefore, two pilot studies in both the U.S. and China were performed.

The pilot study in the U.S. recruited undergraduate students from a large southern public university. As discussed above, undergraduate students have adequate skills related to using different mobile computing devices. They are also familiar with the usage of such devices for their course-related work. To alleviate the potential problem of the lack of working experience, the pilot study used the classroom to simulate the students' "work environment". Participants were asked to consider their jobs as obtaining their college degree and to view their classroom, classmates, and professors as the organization, coworkers, and supervisors respectively. In this way, the students can relate the job-required information processing activities to their own study, which will provide more accurate and relevant data for the analysis.

The survey questionnaire was deployed using Qualtrics^{TM}. The link to the online survey was provided to 283 undergraduate students. All participants were randomly assigned into one of the three types of mobile computing devices: smartphone (69 cases), tablet computer (70 cases), and laptop computer (68 cases) for CGS_{Device} and CCS_{Device} measures. By the survey closing time, 212 responses were received (207 complete responses), yielding a response rate of 74.91%.

Among all participants, there were 90 females (44%) and 115 males (56%). The majority of participants, 184 (86.79%), were between 18 and 22 years of age. Overall, the participants' experiences of using each type of mobile device are shown below:

Time of usage	Less than 1 month	1 to 3 months	3 to 6 months	6 to 12 months	12 to 24 months	more than 24 months	Total responses
Smartphone	12	0	3	7	8	174	202
Tablet Computer	61	14	10	24	26	66	201
Laptop Computer	7	1	1	3	9	181	204

Table 4-4. User experiences across mobile computing devices

The average time of usage with smartphones and laptop computers was around 12 to 24 months. However, the average time with tablet computers was less than 6 months. This reflects the actual marketplace development of these devices: smartphones and laptop computers are more widespread than tablet computers. The distribution of participants' majors were Marketing 60 (28.99%), Finance 44 (21.16%), Accounting 35 (16.91%), Management 31 (14.98%), Insurance and Risk Management 8 (3.86%), MIS 7 (3.38%), Other/Undeclared 20 (9.66%), Did not respond 2 (0.97%).

After removed missing data, the U.S. pilot study sample contained 182 valid responses. The commonly accepted guideline for sample size of a multiple regression analysis is that researchers should have at least five times as many participants as predictor variables. The current study's model has five predictor variables. Since this study utilizes Confirmatory Factor Analysis (CFA) to assess the convergent validity and discriminant validity of all scales, the minimum requirement is five cases per scale item. As a result, given there are 33 items, at least 165 responses were needed for CFA. The U.S. pilot study had a good sample size to perform both the multiple regression analysis and CFA.

The reliability, convergent validity, and discriminant validity of the measurement scales were analyzed using Cronbach's alpha, CFA, and correlation analysis. For the newly developed IPSI measurement scale, the instrument refinement process already demonstrated its content validity. The revised scale was analyzed using pilot study data to gain more confidence in the resulting multi-item scale.

3.2 Reliability Analysis

The reliability of a measurement scale refers to the internal consistency of the measurement scale's items. The current study uses Cronbach's alpha as an indicator of the reliability of the survey instrument. Table 4-5 below provides the summary of Cronbach's alpha coefficients for all measurement scales in the pilot study.

Scale Name	Cronbach's Alpha	With one item deleted	After removing missing values, etc.	With one item deleted
CGS_{Device}	0.772	0.742	0.783	0.765
CCS_{Device}	0.797	0.865 CCSD4	0.812	0.866 CCSD4
CGS_{Job}	0.732	0.748 CGSJ3	0.757	0.794 CGSJ3
CCS_{Job}	0.735	0.795 CCSJ3	0.787	0.840 CCSJ3
MCS	0.841	0.846 MCS2	0.835	0.819
MCD	0.872	0.877 MCD2	0.831	0.840 MCD2
SI	0.792	0.865 SI1	0.770	0.848 SI1
MCSE	0.787	0.839 MCSE4	0.743	0.833 MCSE4
AI	0.918	0.917	0.908	0.904

Table 4-5. U.S. pilot study reliability assessment

As the results show, the Cronbach's alphas of all measurement scales were greater than 0.70. That indicated the measurement scales have a good level of reliability. The results obtained by deleting all possible disturbances such as short survey finish time, short experience using mobile computing devices and missing values are also very similar.

As indicated by these results, the third item in the CGS_{Job} and CCS_{Job} measures was the main cause of the lower alphas. This potentially problematic item was about activities related to social network and other web pages. Since most of the participants primarily use social networks for entertainment purposes, they might be confused about the use of such networks during work. In fact, the participants' comments clearly showed that most of them thought using mobile devices could be a distraction if the user cannot separate personal and work-related usages including social networks such as Facebook and twitter. However, depending on the industry, generating and consuming content on social networks and other web pages can be an important part of professional jobs.

3.3 Validity Analysis

The content validity of the IPSI scale is established through the instrument refinement process. Other measurement scales were adopted from well-established research, lending the measurement scales high levels of content validity. To assess the convergent validity and discriminant validity of all scales, a Confirmatory Factor Analysis (CFA) was conducted using the SPSS AMOS package. Convergent validity refers to the idea that items measuring the same construct should have a high correlation. Discriminant validity refers to the idea that items measuring different constructs should have a low correlation.

In the CFA, the two types of construct validity can be assessed by examining the factor loadings. If items measuring the same construct load on the same factor with factor loadings greater than 0.50, a high level of convergent validity is achieved. If items measuring different constructs do not load on the same factor, a high level of discriminant validity is demonstrated. An item that has low loading on its corresponding factor or an item that cross-load on more than one factor indicates potential problems with the measurement scale's convergent validity and discriminant validity. Table 4-6 below summarizes the CFA factor loading results.

Latent Variable	*Indicators*	*Standardized Loadings (33 indicators)*	*Standard Errors*	*t Values*
CGS_{Device}	CGSD1	0.799	0.039	20.727
	CGSD2	0.642	0.052	12.381
	CGSD3	0.739	0.044	16.655
	CGSD4	0.629	0.054	11.587
CCS_{Device}	CCSD1	0.901	0.023	40.118
	CCSD2	0.800	0.032	25.138
	CCSD3	0.865	0.026	33.919
	CCSD4	***0.421***	***0.065***	***6.489***
CGS_{Job}	CGSJ1	0.857	0.029	29.497
	CGSJ2	0.819	0.032	25.428
	CGSJ3	***0.384***	***0.068***	***5.632***
	CGSJ4	0.526	0.059	8.919
CCS_{Job}	CCSJ1	0.892	0.024	36.662
	CCSJ2	0.855	0.027	31.325
	CCSJ3	***0.358***	***0.069***	***5.199***
	CCSJ4	0.580	0.054	10.796
MCS	MCS1	0.839	0.028	29.958
	MCS2	0.661	0.046	14.297
	MCS3	0.873	0.025	35.188
MCD	MCD1	0.842	0.027	31.408
	MCD2	0.719	0.040	18.136
	MCD3	0.928	0.019	47.964
SI	***SI1***	***0.365***	***0.069***	***5.303***
	SI2	0.712	0.042	16.820
	SI3	0.901	0.028	31.913
	SI4	0.853	0.031	27.544
MCSE	MCSE1	0.785	0.035	22.254
	MCSE2	0.811	0.033	24.850
	MCSE3	0.777	0.036	21.552
	MCSE4	***0.481***	***0.062***	***7.723***
AI	AI1	0.841	0.025	33.134
	AI2	0.926	0.017	55.139
	AI3	0.906	0.019	48.611

Table 4-6. U.S. pilot study CFA loadings (loadings smaller than 0.50 are highlighted)

The cross-loading results indicated that there were a few items cross-loaded on more than one constructs. However, the factor loadings of these items on other constructs were all smaller than 0.5 and smaller than the loadings on their corresponding constructs. Therefore, the cross loading was not deemed to be a significant problem. The CFA results indicated a few items that need revisions. These items are presented in Table 4-7.

Item	Wordings in the survey instrument	Factor loadings
CCSD4	The [mobile device] is capable of performing content-consumption-related tasks at work.	0.421
CGSJ3	My job frequently requires me to create/edit content on social network and other web pages.	0.384
CCSJ3	My job frequently requires me to read content on social network and other web pages.	0.358
SI1	A large portion of my coworker(s) and my supervisor(s) are using the [mobile device].	0.365
MCSE4	I feel confident in fixing problems about the [mobile device].	0.481

Table 4-7. Items with low factor loadings

One possible explanation for the low factor loadings of the “overall” items measuring the content generation/consumption scores (CCSD4) is the wordings of these items. The initial items used terms that were more abstract and passive in nature that may have caused some confusion among the student participants. The CGSJ3 and CCSJ3 items had some problems that were related to the term “social network”. According to the comments gathered from the participants, a large portion of them mentioned, “using mobile devices may cause distractions in the work such as getting on social media, always on Facebook, etc.” Therefore, the term social network needed to be clarified and restricted to professional social networking.

The SI1 and MCSE4 items were different comparing to the rest of items in their corresponding scales. Therefore, these items were revised/dropped from the final instrument list. The modifications to the survey instrument are discussed in the instrument revisions section.

	Mean	S.D.	X1	X2	X3	X4	X5	X6	X7	X8	X9
CGSD	23.64	3.96	**0.79** **0.49**	0.30	0.06	0.13	0.23	0.21	0.03	0.19	0.13
CCSD	24.86	3.21	0.54	**0.81** **0.49**	0.08	0.08	0.25	0.15	0.04	0.19	0.17
CGSJ	22.12	4.14	0.25	0.28	**0.76** **0.49**	0.57	0.08	0.03	0.02	0.09	0.06
CCSJ	20.27	4.49	0.36	0.28	0.76	**0.78** **0.49**	0.06	0.02	0.01	0.03	0.01
MCS	5.73	1.04	0.48	0.50	0.29	0.24	**0.79** **0.49**	0.55	0.13	0.38	0.34
MCD	2.57	1.34	-0.45	-0.39	-0.18	-0.14	-0.74	**0.80** **0.49**	0.11	0.29	0.28
SI	4.35	1.21	0.17	0.19	0.15	0.09	0.36	-0.34	**0.80** **0.49**	0.15	0.09
MCSE	5.61	0.93	0.44	0.44	0.30	0.16	0.62	-0.54	0.39	**0.80** **0.49**	0.42
AI	5.74	1.15	0.37	0.41	0.24	0.12	0.58	-0.53	0.30	0.64	**0.82** **0.49**

Table 4-8. U.S. pilot study discriminant analysis, the diagonal shows the composite reliability (CR, top) and average variance extracted (AVE, below)

Overall, the initial survey items list exhibited acceptable levels of reliability, content validity, convergent validity, and discriminant validity. The next section discusses the U.S. pilot study data analysis.

3.4. U.S. Pilot Study Results

The newly developed IPSI scale uses four sets of aggregated scores to calculate the final index score. The CGS_{Device} and CCS_{Device} are measuring perceived device capabilities in content generation and consumption, while the CGS_{Job} and CCS_{Job} are measuring perceived job requirements in content generation and consumption. These scores were used to calculate the content generation score (CGS) and content consumption score (CCS) to indicate how well employees perceive a device's capabilities can support their job-required content generation and consumption activities. Then the CGS and CCS were used together with the weights of these activities at work to form the final IPSI score. Table 4-9 shows the IPSI framework statistics in the U.S. pilot study data.

Mean Score	**CGS_{Device}**	**CCS_{Device}**	**CGS_{Job}**	**CCS_{Job}**	**CGS**	**CCS**	**IPSI**
Smartphone (S)	21.754	24.508	19.377	22.016	1.099	1.104	12.550
Tablet computer (T)	25.705	25.705	21.000	22.230	1.196	1.145	13.824
Laptop computer (L)	23.450	24.350	20.433	22.100	1.126	1.094	12.797
All	23.637***	24.857***	20.269***	22.115***	1.140**	1.114**	13.059
S-T	-3.951***	-1.197**	-1.623*	-0.213	-0.097***	-0.041	-1.274***
S-L	-1.696**	0.158	-1.056	-0.084	-0.027	0.010	-0.247
T-L	2.255***	1.355**	0.567	0.130	0.070*	0.051	1.027**
Range	**CGS_{Device}**	**CCS_{Device}**	**CGS_{Job}**	**CCS_{Job}**	**CGS**	**CCS**	**IPSI**
Smartphone	8-28	15-28	6-26	8-28	0.75-1.63	0.63-1.71	7.44-18
Tablet computer	4-28	16-28	4-28	4-28	0.50-1.83	0.92-1.96	3.79-19.25
Laptop computer	12-28	7-28	6-28	8-28	0.79-1.92	0.54-1.83	4.73-18
All	4-28	7-28	4-28	4-28	0.5-1.92	0.54-1.96	3.79-19.25

Table 4-9. IPSI framework statistics of U.S. pilot study (* $p<0.10$ ** $p<0.05$ *** $p<0.01$)

A comparison of the means of these scores showed that the three types of mobile devices differ in their CGS_{Device} and CCS_{Device} measures. In terms of the perceived content-generation capabilities, the U.S. pilot study data showed that the tablet computer had the highest and the smartphone had the lowest mean score. In terms of perceived content-consumption capabilities, the tablet computer had the highest and the laptop computer had the lowest mean score. The mean scores were significantly different from each other for all three types of mobile devices in content generation. In content consumption, the mean score of the tablet computer was significantly different from the other two types of devices.

Overall, the means of CGS and CCS were significantly different from each other, indicating that the IPSI measure can distinguish between the two underlying constructs and can reflect the different perceived device capabilities and job requirements. However, the tablet computer results need a further analysis. As shown in Table 4-9, the mean scores of CGS_{Device}

and CCS_{Device} are essentially the same for the tablet computers. In other words, on average the participants thought tablet computers had similar capabilities to perform both types of activities. This result could be influenced by the usage of various accessories such as Bluetooth keyboards, stylus pens, and other input devices. The pilot survey instrument did not specify whether these accessories were to be considered when answering the questions. Therefore, in the final survey instrument, one new item was added to measure the usage of different accessories for all three types of mobile devices.

Next, multiple regression and mediation analyses were performed using the U.S. pilot study data in order to test the hypotheses in the measurement model.

3.4.1. Multiple Regression analysis:

First, a multiple regression analysis was performed. Model 1 specified the mobile-computing-device-adoption intentions (AI) as a dependent variable and the IPSI, SI, and MCSE as independent variables. Model 2 added the mobile computing satisfaction (MCS) and dissatisfaction (MCD) to the independent variable list. The regression results are shown below.

Model #	Model F	Adj. R Square	F Change	IPSI	SI	MCSE	MCD	MCS
1	46.050***	0.427	46.050***	0.141**	0.061	0.582***		
2	33.031***	0.469	8.039***	0.077	0.016	0.432***	0.200**	-0.114

Table 4-10. U.S. pilot study regression analysis summary (** $p<0.05$; *** $p<0.01$)

Both models were significant ($p<0.001$). In model 1, coefficient analysis showed both IPSI and MCSE have significant positive associations with AI. However, SI's association with AI is not significantly different from zero. In model 2, after the two mediators were added, the model adjusted R-squared statistics increased from 0.427 to 0.469 and was significant at the $p<0.001$ level. This indicated that the additional variables contributed to explaining significantly more total model variance. The MCS has a significant effect in model 2. Coefficient analysis showed some evidences that IPSI's effect on AI is mediated by MCS and MCD. However, since MCS and MCD were correlated, there were some multicollinearity issues in model 2. As a result, the multiple regression analysis showed some support for Hypotheses 1 and 5 in the model. Due to the multicollinearity issues and the nature of Hypotheses 2 and 3, a mediation analysis was needed to examine the two proposed mediators together even when there was some evidence in model 2 that showed some support for the mediating effects.

3.4.2 Mediation analysis

In order to test the two mediation hypotheses in the model, the U.S. pilot study followed the procedure suggested by Baron and Kenny (1986). The mediation analysis had three steps: first, test the main effect of independent variable IPSI on the dependent variable AI; second, test the effect IPSI has on both mediators -- mobile computing satisfaction (MCS) and mobile computing dissatisfaction (MCD); third, test the effects the mediators have on the dependent variable AI. MCS and MCD are mediating the relationship between the IPSI and AI If steps 1 and 2 discover that the independent variable IPSI significantly affects AI, MCS, and MCS, and step 3 discovers that after including the MCS and MCD, the main effect of IPSI on AI was reduced. This study used the PROCESS macro to test the mediations (Hayes, 2013).

Model	**R square**	**F**	**IPSI**	**MCS**	**MCD**
1 IPSI →MCS	0.1381	28.84***	0.1447***		
2 IPSI →MCD	0.0995	19.88***	-0.1584***		
3 IPSI, MCS, MCD →AI	0.3692	34.73***	0.0412	0.4429***	-0.1706**

Table 4-11. U.S. pilot study mediation analysis results (** p<0.05; *** p<0.01)

The mediation analysis results showed that IPSI had significant associations with both MCS and MCD. Furthermore, the significant association between IPSI and AI was mediated by MCS and MCD. The regression coefficient of MCD was negative, which indicated there was a negative association between IPSI and MCD and a negative correlation between MCD and AI.

Hypotheses 2 and 3 were supported by the mediation analysis. The positive relationship between IPSI and AI was mediated by both MCS and MCD.

Note that although mobile computing satisfaction and dissatisfaction are correlated, they exhibited different effects on employees' adoption intentions. According to the mediation analysis, mobile computing satisfaction had a larger effect than dissatisfaction. A complete output of SPSS multiple regression analysis and mediation analysis can be found in Appendix C.

Overall, the pilot study found some preliminary support for four of the five hypotheses proposed in the measurement model. Since Hypothesis 4 was about social influence, given the participants' lack of work experience, the result might be expected. In the main study, participants were all working adults. Their responses were more relevant in assessing the social influence factor on their mobile-computing-device-adoption intentions. Table 4-12 shows a summary of the hypotheses testing results and Figure 4-2 illustrates the hypotheses testing results in the measurement model.

Hypotheses	Regression coefficient	Hypotheses Testing
H1: The IPSI has a positive association with an employee's mobile-computing-device-adoption intention.	0.136**	Supported
H2: Mobile-computing satisfaction mediates the positive relationship between the IPSI and an employee's mobile-computing-device-adoption intention.	0.419**	Supported
H3: Mobile-computing dissatisfaction mediates the positive relationship between IPSI and an employee's mobile-computing-device-adoption intentions.	-0.186**	Supported
H4: Social influence of mobile computing devices has a positive association with an employee's mobile computing-device-adoption intention.	0.063	Not supported
H5: An employee's Mobile Computing Self-Efficacy (MCSE) has a positive association with his/her mobile-computing-device-adoption intention.	0.582***	Supported

Table 4-12. Summary of U.S. pilot study hypotheses testing results (** $p<0.05$; *** $p<0.01$)

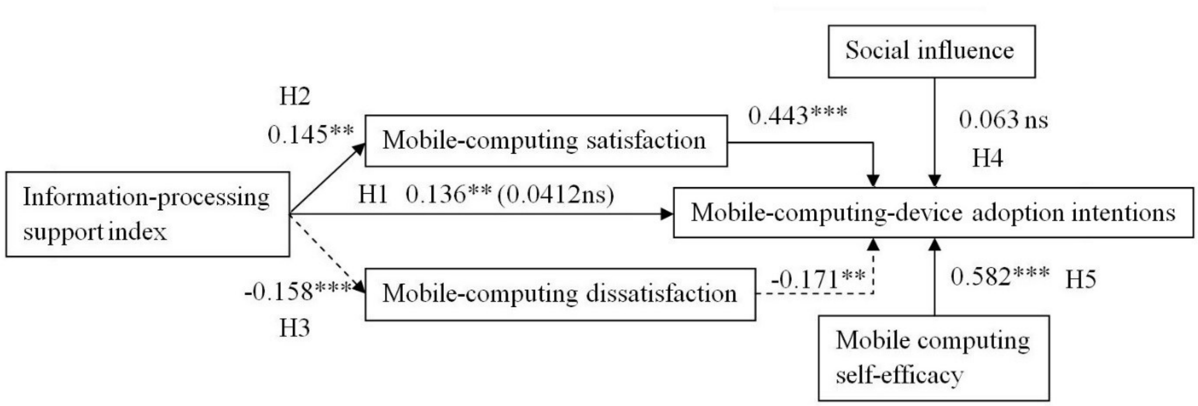


Figure 4-2. Measurement model with U.S. pilot study hypothesis testing results

3.5. Chinese Pilot Study Results

The current research conducted a second pilot study in China to further assess the reliability and validity issues of the measurement scales and to prepare for the main study data collection. The same survey questionnaire was translated into Chinese by a double translation process, which is discussed later in the main study. 33 MBA students (21 males) from a large public Chinese university participated in the Chinese pilot study. Of all the participants, 15 were between 23 and 30 years of age, 17 were between 31 and 54 years of age. Most of the participants had more than one year of work experience. Since this is a very small sample, participants were asked to fill out surveys regarding all three types of mobile computing devices. Therefore, the data set contained 99 total responses.

The IPSI framework statistics for the Chinese pilot study are presented in Table 4-13 below. Since participants filled out all three devices versions, the device specific comparisons between job-related measures are not applicable.

Mean Score	**CGS_{Device}**	**CCS_{Device}**	**CGS_{Job}**	**CCS_{Job}**	**CGS**	**CCS**	**IPSI**
Smartphone (S)	18.939	22.455	N/A	N/A	0.808	0.939	7.799
Tablet computer (T)	22.697	24.303	N/A	N/A	0.956	1.016	10.112
Laptop computer (L)	26.697	26.515	N/A	N/A	1.131	1.109	13.778
All	22.78***	24.42***	23.55	23.91	0.968**	1.022**	10.563
S-T	-3.758***	-1.848**	N/A	N/A	-0.157***	-0.077	-2.476**
S-L	-7.758***	-4.061***	N/A	N/A	-0.323***	-0.169***	-5.979***
T-L	-4.000***	-2.212***	N/A	N/A	-0.167***	-0.092*	-3.666***
Range	**CGS_{Device}**	**CCS_{Device}**	**CGS_{Job}**	**CCS_{Job}**	**CGS**	**CCS**	**IPSI**
Smartphone	9-28	11-28	N/A	N/A	0.42-1.25	0.33-1.46	2.17-14.28
Tablet computer	9-28	16-28	N/A	N/A	0.50-1.42	0.58-1.58	2.93-17.22
Laptop computer	20-28	18-28	N/A	N/A	0.71-1.42	0.58-1.58	4.20-20.72
All	9-28	11-28	16-28	14-28	0.42-1.42	0.33-1.58	2.17-20.72

Table 4-13. IPSI framework statistics of Chinese pilot study (* p<0.10 ** p<0.05 *** p<0.01)

Analysis demonstrated that the three types of mobile computing devices differ from each other in terms of their perceived capabilities to support work-required content generation and consumption activities. The scores for smartphones were lowest while scores for laptop computers were highest. These results showed additional support that the IPSI could capture the differences between these devices, and distinguish them in terms of their perceived capabilities to support employees' job-related information processing needs.

Similar to the U.S. pilot study, Cronbach's alphas were used to assess the reliability of all measurement scales. The Cronbach's alphas were greater than 0.70 for all but the CGS_{Job} scale.

Scale Name	Cronbach's Alpha	With one item deleted
CGS_{Device}	0.910	0.906
CCS_{Device}	0.852	0.878 CCSD4
CGS_{Job}	0.639	0.633
CCS_{Job}	0.752	0.758 CCSJ2
MCS	0.750	0.744
MCD	0.760	0.727
SI	0.727	0.899 SI1
MCSE	0.881	0.879 MCSE1
AI	0.871	0.860

Table 4-14. Chinese pilot study reliability analysis

The reliability analysis showed that these items had acceptable levels of reliability. Since the dataset was too small, CFA was not performed. Overall, these results showed that the survey items were measuring their underlying constructs consistently. The language differences were not affecting the validity of the results.

Similarly, multiple regression and mediation analyses were performed to gather empirical evidence about hypotheses in the model. Table 4-15 summarizes these results:

Model #	**Model F**	**Adjusted R Square**	**IPSI**	**SI**	**MCSE**	**MCD**	**MCS**
1	8.391***	0.185	0.253**	0.107	0.245**		
2	3.144**	0.220	0.160	0.101	0.166	0.103	-0.186
Mediation	**IPSI**		**IPSI**		**IPSI**	**MCS**	**MCD**
IPSI→MCS	0.134***	IPSI→MCD	-0.141***	All	0.0475**	0.145	-0.138

Table 4-15. Chinese pilot study results (** $p<0.05$ *** $p<0.01$)

Because of the small sample size, these tests did not have much power. However, the results still showed that IPSI and MCSE had strong positive associations with AI.

3.6. Instrument Revisions

Based on the analyses above, the following survey items in the IPSI scale were revised.

Items related to social network: CGSD3, CCSD3, CGSJ3, and CCSJ3

The CGSJ3 and CCSJ3 had low factor loadings in the CFA. In addition, as indicated by the Cronbach's alpha, they were causing a reduced alpha coefficient. As discussed above, the potential problem was the confusion of work-related social networking and social media. Therefore, the revised items used "professional social network" instead of just "social network" in all items that contain social network.

“Overall” items: CGSD4, CCSD4, CGSJ4, and CCSJ4

These items all had low factor loadings in the CFA. CCSD4 was also causing a reduced alpha coefficient for the scale. The potential issue in these items was the abstract and passive term content-generation/consumption-related tasks. The revised items used “tasks that generate/consume content for/from others” instead of “content-generation/consumption-related tasks” to avoid these problems.

Accessory Usage

As discussed above, the usage of various types of accessories such as Bluetooth keyboards, stylus pens, and others may affect employees’ perceptions about the mobile computing devices’ capabilities to support the content generation and consumption activities at work. For example, people may use a Bluetooth keyboard to increase the tablet computer’s capabilities to perform tasks that require them to generate content. Employees may have the perceptions that the mobile computing device could not fulfill their information-processing needs because they have to use these accessories to help. On the other hand, they may also have the perception that their mobile computing devices can fulfill their information-processing needs because they consider the device and accessories together. Therefore, the usage of these accessories could influence employees’ CGS_{Device} and CCS_{Device} scores. To capture this valuable information, an item measuring the participants’ accessory usage was added to the final survey instrument.

Items in other scales

Although the MCS and MCD items demonstrated acceptable levels of reliability and appropriate factor loadings in CFA, a review of these scales found that the second item was different from the rest items. In the main study, this could potentially cause inconsistent responses. As a result, the MCS2 and MCD2 items were changed to “The [mobile device] makes it easier for me to complete my job.” and “The [mobile device] does not make it easier for me to complete my job.”

In both the Cronbach’s alphas and CFA, SI1 and MCSE4 were causing low alpha coefficients and had low factor loadings. A review of those two items showed that they were very different from the rest of the items in their corresponding scales. Therefore, in the final survey instrument, the SI1 was modified to “Using the [mobile device] is considered normal in my organization”, and the MCSE4 was dropped.

As a result, the revised final survey instrument contained 34 items. Appendix B shows the complete survey questionnaire used in the main study.

4. Main study

4.1. Introduction

The main study data collection was conducted at a large public university in the central part of China. As introduced earlier, the Chinese university just launched a university-wide program to manage its employees’ smartphone adoptions. Therefore, this is a great opportunity to examine how the proposed IPSI construct would affect the employees’ mobile-computing-device-adoption intentions. The final instrument used paper-based survey questionnaires. Before distributing these surveys to the main study participants, a double translation process was performed to ensure the language barrier does not cause problems in the final data collection.

4.2. Double translation process

In the double translation process, the final survey questionnaire was translated into Chinese and sent to the Chinese university. One faculty member at the Chinese university translated the Chinese version survey questionnaire back to English. The two versions of the survey were then compared and any discrepancies were resolved. During this process, survey items related to professional social network websites appeared to be problematic in the Chinese context. In China, professional social network websites such as LinkedIn and others are not as popular as they are in the U.S. When people see the term social network websites, they tend to think about recreational social network sites. Therefore, social networking was not considered as one of the job-required activities. In order to assess job-related networking activities, the final survey changed all items using the "professional social network websites" to "work-related web pages" to capture the most complete and relevant information. After the Chinese version of the survey questionnaire was validated, paper-based final survey questionnaires were distributed to all faculty and staff members in nine schools of the Chinese university during their weekly staff meetings.

4.3. Main study survey distribution

In total, 393 survey questionnaires were distributed. By the survey deadline, 335 responses were received, yielding a response rate of 85.24%. Among all responses, 317 were complete. An initial analysis of all responses showed that some of them were problematic. For example, mobile computing satisfaction and dissatisfaction were measured using six items. These items were all coded the same way. It is very unlikely that a respondent will have exactly the same answers in all six items. Obviously, employees cannot be both highly satisfied and highly dissatisfied about their mobile computing needs in their organizations. In addition, the exact same answers in all six items indicated that the respondent probably was not paying much attention while answering the survey.

These responses were introducing noise into the dataset. Therefore, all problematic responses such as the ones that answered all survey questions with the same answers and the ones that answered the six satisfaction and dissatisfaction items with the same answers were removed from the final analysis. In this way, the current research was able to obtain the maximum number of responses and limit the risk of noisy data. The final data set contained 266 valid responses.

4.4. Reliability analysis

A reliability analysis was conducted using Cronbach's alpha. Table 4-16 below summarizes the alpha coefficients for all constructs in the model.

Scale	CGS_{Device}	CCS_{Device}	CGS_{Job}	CCS_{Job}	MCS	MCD	SI	MCSE	AI
Cronbach's Alpha	0.911	0.893	0.881	0.889	0.786	0.809	0.743	0.871	0.906

Table 4-16. Main study reliability analysis

As the results show, all the Cronbach's alphas are above 0.75 except SI (0.743), which means all the items have high levels reliability measurements except Social Influence (SI). In the following sections, the first item measuring the SI construct was found to have very low factor loading. After removing that item, the Cronbach's alpha for SI increases to 0.844.

Overall, these results showed that items in the main study survey possess adequate levels of reliability. They were measuring their underlying constructs consistently. Next, a confirmatory factor analysis (CFA) was performed to assess the discriminant and convergent validity of these survey items.

4.5 Validity analysis

As discussed above, the content validity of all survey items was initially assessed during the instrument development process. Table 4-17 shows the CFA factor loadings.

Latent Variable	*Indicators*	*Standardized Loadings (32 indicators)*	*Standard Errors*	*t Values*
CGS_{Device}	CGSD1	0.889	0.016	55.743
	CGSD2	0.884	0.016	53.996
	CGSD3	0.822	0.022	36.719
	CGSD4	0.800	0.025	32.605
CCS_{Device}	CCSD1	0.819	0.023	35.330
	CCSD2	0.864	0.019	45.798
	CCSD3	0.861	0.019	44.736
	CCSD4	0.764	0.028	26.999
CGS_{Job}	CGSJ1	0.819	0.024	34.320
	CGSJ2	0.878	0.019	47.468
	CGSJ3	0.747	0.030	24.634
	CGSJ4	0.793	0.026	30.261
CCS_{Job}	CCSJ1	0.805	0.025	32.426
	CCSJ2	0.853	0.020	41.712
	CCSJ3	0.836	0.022	37.970
	CCSJ4	0.780	0.027	28.666
MCS	MCS1	0.614	0.041	14.880
	MCS2	0.802	0.026	30.398
	MCS3	0.804	0.026	30.781
MCD	MCD1	0.605	0.044	13.628
	MCD2	0.790	0.033	23.681
	MCD3	0.905	0.029	30.875
SI	***SI1***	***0.220***	***0.062***	***3.537***
	SI2	0.841	0.027	31.031
	SI3	0.898	0.025	36.606
	SI4	0.684	0.038	18.220
MCSE	MCSE1	0.744	0.030	24.531
	MCSE2	0.855	0.020	42.346
	MCSE3	0.906	0.016	56.957
AI	AI1	0.841	0.020	41.758
	AI2	0.917	0.014	66.365
	AI3	0.869	0.018	48.221

Table 4-17. Main study CFA loadings (loadings smaller than 0.50 are highlighted)

The CFA results revealed that most items loaded properly (greater than 0.50) on their underlying constructs. However, there were problems in the SI1 and AI1 items. The SI1 item failed to load on its own construct (factor loading is 0.220 which is less than 0.50). This indicated that SI1 was not measuring the SI construct consistently with the other items. It should be dropped in the data analysis. The Cronbach's alpha of the SI construct also increased from 0.743 to 0.844 after dropping that item.

Item AI1 loaded on both AI and MCSE. The factor loading on MCSE was greater than 0.50, which indicated the item was measuring the MCSE construct more than the AI construct. As a result, the item AI1 was also dropped in the final analysis. The Cronbach's alpha of AI after dropping AI1 decreased a little from 0.906 to 0.902. In addition, the cross loading of AI1 may suggest that there were some common method variance issues among these items since they were all measured with paper-based surveys. Chapter V discusses the issue of common method variance/biases in more detail.

	Mean	**S.D.**	**X1**	**X2**	**X3**	**X4**	**X5**	**X6**	**X7**	**X8**	**X9**
CGSD	20.63	5.82	**0.91** **0.72**	0.67	0.27	0.27	0.53	0.06	0.11	0.35	0.36
CCSD	22.26	4.95	0.82	**0.90** **0.69**	0.27	0.35	0.50	0.08	0.12	0.32	0.37
CGSJ	21.31	5.06	0.52	0.52	**0.88** **0.66**	0.60	0.32	0.01	0.10	0.30	0.29
CCSJ	23.07	4.32	0.52	0.59	0.77	**0.89** **0.67**	0.32	0.02	0.10	0.28	0.37
MCS	5.11	1.21	0.73	0.71	0.57	0.57	**0.79** **0.56**	0.11	0.15	0.42	0.45
MCD	3.59	1.41	-0.25	-0.28	-0.09	-0.12	-0.34	**0.82** **0.60**	0.00	0.04	0.03
SI	4.34	1.15	0.34	0.35	0.31	0.31	0.39	0.06	**0.78** **0.51**	0.29	0.16
MCSE	4.93	1.30	0.59	0.57	0.54	0.53	0.65	-0.19	0.54	**0.88** **0.70**	0.61
AI	5.42	1.28	0.60	0.61	0.54	0.61	0.67	-0.16	0.40	0.78	**0.91** **0.77**

Table 4-18. Main study discriminant analysis, the diagonal shows the composite reliability (CR, top) and average variance extracted (AVE, below)

Item correlations are shown on the lower matrix while squared correlations are shown on the upper matrix. Discriminate validity is shown by comparing the average variance extracted (AVE) to the squared correlation. If AVE exceeds the squared correlation, discriminant validity is demonstrated (Fornell and Larcker, 1981).The reliability and validity analyses above showed that the survey items exhibit adequate levels of reliability and validity and the language differences did not appear to influence the validity of the measures.

4.6. Main study results

As introduced above, the final data set contained 266 cases. All participants were randomly assigned into one of the three versions of mobile computing devices in the survey: smartphones (97 cases), tablet computers (84 cases), and laptop computers (85 cases). There were 121 females (45.83%) and 143 males (54.17%). The majority of participants, 190 (71.43%) were between 31 and 54 years of age. The final dataset was analyzed with SPSS and SAS. Table 4-19 summarizes the demographics statistics of the main study.

	Gender		**Age**					**Device**		
	Male	Female	18-22	23-30	31-54	55-64	>64	Smartphone	Tablet computer	Laptop computer
Cases	143	121	2	55	190	14	4	97	84	85
%	54.2	45.8	0.8	20.7	71.4	5.3	1.5	36.5	31.6	32.0

Table 4-19. Demographic statistics of main study

4.6.1. IPSI Framework Analysis

First, the new scale IPSI was calculated using the two sets of aggregated scores: CGS and CCS. As shown in Table 4-20, the IPSI framework captured the differences among three types of mobile computing devices in their perceived capabilities to support job-required information processing activities. The CGS_{Device} and CCS_{Device} captured the differences in employees' perceptions about how different devices are able to perform content generation/consumption activities at work. In contrast to the U.S. pilot study results, where the tablet computers had the highest CGS and CCS scores, there is an order of smartphone → tablet computer → laptop computer when comparing the Chinese respondents' perceptions about the devices' capabilities in performing these tasks.

Mean Scores	CGS_{Device}	CCS_{Device}	CGS_{Job}	CCS_{Job}	CGS	CCS	IPSI
Smartphone (S)	18.64	21.33	21.55	22.74	0.7875	0.8785	8.944
Tablet computer (T)	19.54	21.33	19.58	21.82	0.9511	0.9295	9.844
Laptop computer (L)	23.99	24.25	22.74	24.68	1.031	0.9539	11.482
All	20.63	22.26	21.31	23.07	0.9169	0.9187	10.0393
S-T	-0.90	0	1.97^{*}	0.92	-0.1636^{***}	-0.051	-0.900^{*}
S-L	-5.35^{***}	-2.92^{***}	-1.19^{**}	-1.94^{***}	-0.2435^{**}	-0.0754^{**}	-2.538^{***}
T-L	-4.45^{***}	-2.92^{***}	-3.16^{***}	-2.86^{***}	-0.0799^{**}	-0.0244	-1.638^{***}

Table 4-20. Main study IPSI framework analysis (* p<0.10 ** p<0.05 *** p<0.01)

As indicated above, the smartphones' perceived capabilities to support job-required information-processing activities are the lowest, while laptop computers' perceived capabilities are the highest. Given the actual developments of these devices in China and the physical limitations of these devices, the IPSI framework results were consistent with the prediction that smartphone and tablet computer may support job-required content consumption activities better than content generation activities. It was also consistent with the prediction that when compared to smartphones, tablet computers have higher capability to support job-required information-processing activities.

In addition, as summarized in Table 4-21, the usage of accessories in general increased the IPSI scores. Chapter V provides detailed discussions about the IPSI measurements and the usage of accessories across different devices.

	N/A	None	Keyboard	Stylus pen	Both	Other	Combined
Cases	30	108	75	19	19	15	128
CGS_{Device}	18.23	19.80	20.97	22.16*	23.79***	23.80**	21.90***
CCS_{Device}	19.30***	22.29	22.11	23.89	24.58**	23.80	22.94
CGS	0.941	0.862	0.963**	0.933	0.944	0.977***	0.957**
CCS	0.905	0.906	0.927	0.991	0.929	0.890	0.932
IPSI	8.385**	9.747	10.278	10.916	11.442**	11.377**	10.674**

Table 4-21. IPSI analysis with accessories (* p<0.10 ** p<0.05 *** p<0.01)

The next sections discuss hypotheses testing using multiple regression and mediation analyses.

4.6.2. Multiple regression analysis

In order to test the proposed hypotheses, a multiple regression analysis was performed. Mobile-computing-device-adoption intentions (AI) was the dependent variable, while IPSI, Social Influence (SI), and Mobile Computing Self-Efficacy (MCSE) were the independent variables in Model 1. In Model 2, Mobile Computing Satisfaction (MCS) and Mobile Computing Dissatisfaction (MCD) were added to the independent variables to test their mediating effects. Table 4-22 presents the summary of the multiple regression analysis results.

Model #	**Model F**	**Adjusted R Square**	**IPSI**	**SI**	**MCSE**	**MCD**	**MCS**
1	116.024***	0.566	0.231***	-0.072	0.639***		
2	78.446***	0.594	0.146***	-0.093**	0.541***	0.258***	0.090**

Table 4-22. Main study multiple regression analysis results (** $p<0.05$ *** $p<0.01$)

These results show that in Model 1, the IPSI and MCSE all have positive associations with the AI construct that are statistically significant at $p<0.01$ level. Therefore, the data provided some empirical support for Hypotheses 1 and 5 in the measurement model. In model two, the mediations effects of MCS and MCD were tested after controlling for all other constructs in the model. As the results show, SI, MCD, and MCS all have significant associations with AI. The results also showed that MCS has a positive significant association with AI. Although IPSI still has a significant association with AI, its magnitude is reduced as revealed in the coefficients.

However, the signs of the SI and MCD regression coefficients are reversed comparing to their zero-order correlations with the AI construct. These results showed that after controlling for all other constructs, SI had a negative association with AI, which was statistically significant at

$p<0.05$ level. MCD had a positive association with AI, which was significant at $p<0.01$ level. Both results were contrary to the proposed hypotheses. Therefore, the data showed only limited empirical support for Hypothesis 2. It appears that MCS partially mediated the positive association between IPSI and AI. Hypotheses 3 and 4 are not supported by the data. These results are interesting. Chapter V provides a more detailed discussion about the reversed coefficient signs and interpretations. The complete SPSS output is attached in Appendix D.

The multiple regression analysis provided some empirical support for three of the five hypotheses in the measurement model. However, in order to assess the two mediation-related hypotheses simultaneously, a mediation analysis using the bootstrap technique was performed.

4.6.3. Mediation analysis

A mediation analysis using the SPSS PROCESS macro (Hayes, 2013) was performed to analyze the two proposed mediators simultaneously and to test the direct and indirect effects among IPSI, MCS, MCD, and AI. As discussed by Hayes (2013), instead of using the terms full mediation and/or partial mediation, the term direct and indirect effects are more relevant. In the discussions of Baron and Kenny (1986), the traditional causal steps analysis requires that there exists a significant effect between the independent variable and dependent variable before we can analyze the mediating effects of the third variables. However, as pointed out by Mackinnon, et al, (2003), Hayes and Preach, (2013), this is not necessary. Hayes (2013) further argued that the usage of mediation should be replaced with conditional process analysis. Therefore, in the mediation analysis, this study adopted the newer approach and used the direct and indirect effects to assess the proposed mediations of MCS and MCD.

Model	R square	F	IPSI	MCS	MCD
1 IPSI →MCS	0.398	174.596***	0.236***		
2 IPSI →MCD	0.075	21.460***	-0.119***		
3 IPSI, MCS, MCD →AI	0.601	78.446***	0.060***	0.280***	0.085**

Table 4-23. Main study mediation analysis results (** p<0.05 *** p<0.01)

As the results in Table 4-23 shows, IPSI had significant associations with AI, MCS, and MCD. After adding the two mediators, the association between IPSI and AI was still significant but the coefficient dropped from 0.236 to 0.060. The total effect was 0.116 and 48.49% of the total effect was due to the indirect effects through MCS and MCD. Therefore, these results suggested that there were significant mediating effects. In the older terms used to describe these types of relationships, MCS partially mediated the positive effect between IPSI and AI. However, the MCD construct had a positive relationship with AI after controlling for SI and MCSE. This indicated that the MCD construct was an inconsistent mediator. As discussed by Mackinnon, et al., (2000), different directions of direct and indirect effects suggested an inconsistent mediator.

Overall, the mediation analysis suggests that there was some empirical support for Hypothesis 2 in the measurement model. The complete mediation analysis output can be found in Appendix D.

4.6.4. Hypotheses testing results

As discussed above, the multiple regression and mediation analysis showed some empirical support for Hypotheses 1, 2, and 5. Social influence construct had a very small effect on AI. After controlling for the MCSE and other constructs, its association with the AI became significantly negative. The mediation analysis provided some support for Hypothesis 2. However, MCD was identified as an inconsistent mediator. It was reducing the total effect of IPSI on AI. Chapter V discusses these issues in more detail. The hypotheses testing results are shown below.

Hypotheses	Regression coefficient	Hypotheses Testing
H1: The IPSI has a positive association with an employee's mobile-computing-device-adoption intention.	0.231***	Supported
H2: Mobile-computing satisfaction mediates the positive relationship between the IPSI and an employee's mobile-computing-device-adoption intention.	0.280***	Supported
H3: Mobile-computing dissatisfaction mediates the positive relationship between IPSI and an employee's mobile-computing-device-adoption intentions.	0.085***	Not Supported
H4: Social influence of mobile computing devices has a positive association with an employee's mobile computing-device-adoption intentions.	-0.093**	Not supported
H5: An employee's Mobile Computing Self-Efficacy (MCSE) has a positive association with his/her mobile-computing-device-adoption intentions.	0.541***	Supported

Table 4-24. Main study hypotheses testing results (** p<0.05; *** p<0.01)

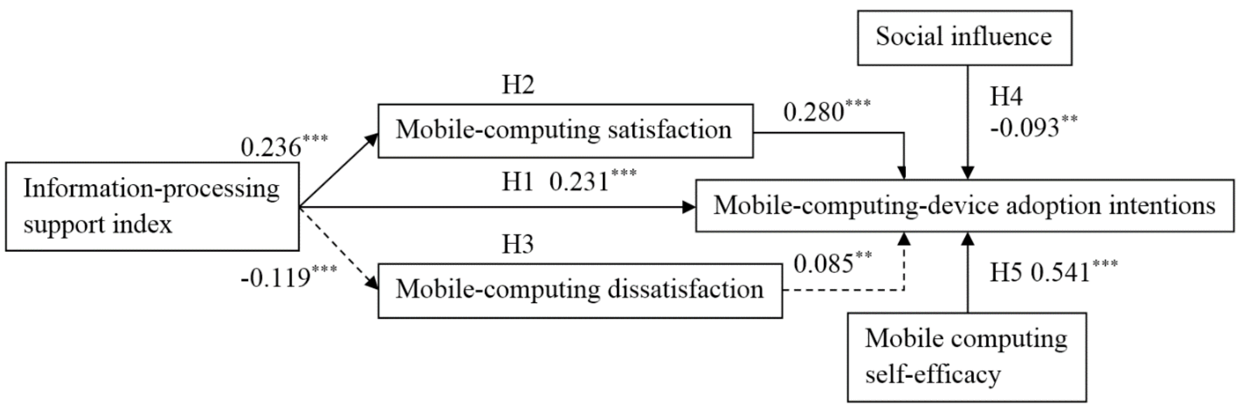


Figure 4-3. Main study hypotheses testing results

5. Chapter Summary

This chapter discussed the IPSI instrument refinement process, the data analysis results of pilot study and main study. The new multi-item scale of IPSI was refined and tested. Cronbach's alpha and CFA were performed to assess the reliability, convergent validity, and discriminant validity of all scales. The two pilot studies provided support for the reliability and validity assessments of these scales. They also gathered initial evidence about the hypotheses testing in the measurement model. Finally, the survey instruments were revised and translated into Chinese via a double translation process. The main study data analysis showed that all scales demonstrated adequate levels of reliability and validity. The hypotheses testing show that there were empirical support for Hypotheses 1, 2, and 5.

Chapter V provides detailed discussions about the IPSI framework across different devices and demographic control variables, the issue about common method variance, and issues about the SI and MCD constructs suggested by the main study data analysis.

CHAPTER V

DISCUSION OF RESULTS

1. Chapter Overview

This chapter discusses the results of the main study. First, the IPSI framework is examined in detail, with an emphasis on the differences of CGS and CCS scores among three types of mobile devices. The impact of accessory usage on these scores is also explored. Next, potential common method variance (CMV) and bias in the main study are evaluated. This chapter assesses the CMV in the data using different techniques and shows the structural equation modeling estimations after controlling for the common method variance. Generally, the CMV did not significantly influence the results of hypotheses testing.

Multiple regression and mediation analyses showed some interesting results about social influence (SI) and mobile computing dissatisfaction (MCD) in Chapter IV. These results are discussed and explored in more detail. Finally, the results of comparing the distributions of all constructs across various demographic variables suggest some interesting research directions for future studies.

2. IPSI Framework

As discussed in previous chapters, the CGS_{Device} and CCS_{Device} scores in the IPSI framework captured how employees are viewing mobile computing devices' capabilities differently in terms of supporting their job-required information-processing activities. The main study data analyses revealed that employees did have different perceptions about different types of mobile devices. Overall, employees' perceptions about the smartphones' capabilities to support information-processing activities at work were the lowest and the perceptions about laptop computers' capabilities were the highest. In terms of supporting content-generation activities, the perceived capabilities of the smartphones, tablet computers, and laptop computers are ranging from the lowest to the highest, respectively. In terms of supporting content-consumption activities, the perceived capabilities of the smartphones and tablet computers were at the same level, while the perceived capabilities of the laptop computers were much higher.

These results are different from the U.S. pilot study data. In the U.S. pilot study, the tablet computers had the highest perceived capabilities to support both types of information-processing activities. In the main study, the survey questionnaires gathered participants' comments about their experiences of using these devices at work. From the comments gathered, the difference in infrastructure development was identified as one important contributor to different device-related IPSI scores. Several participants mentioned that they hoped the employer could build more wireless access points to facilitate their devices usage. Given the fact that the Chinese university did not have full Wi-Fi coverage on campus and the significantly slower network connection speed, the tablet computers' performance was limited in the Chinese university context. For example, in U.S., tablet computers can perform a much wider range of tasks since many applications rely on readily available network connections. Without network support, tablet computers only have limited processing power and physical memory. As a result, the perceived capabilities of tablet computers were much lower in the main study.

2.1. The usage of accessories

As discussed in the pilot study analysis, employees utilized different accessories when using their mobile computing devices at work. These accessories can help enhancing the devices' capabilities to perform work-related information-processing activities. Therefore, accessory usage may influence employees' perceptions about their devices' information processing support capabilities. The main study captured this information by asking the participants to indicate the types of accessory they adopt when using their mobile devices at work. Table 5-1, 5-2, 5-3, and 5-4 below summarize the results.

	N/A	None	Keyboard	Stylus pen	Both	Other	All Acc.
Cases	30	108	75	19	19	15	128
CGS_{Device}	18.23	19.80	20.97	22.16^{*}	23.79^{***}	23.80^{**}	21.90^{***}
CCS_{Device}	19.30^{***}	22.29	22.11	23.89	24.58^{**}	23.80	22.94
CGS	0.941	0.862	0.963^{**}	0.933	0.944	0.977^{***}	0.957^{**}
CCS	0.905	0.906	0.927	0.991	0.929	0.890	0.932
IPSI	8.385^{**}	9.747	10.278	10.916	11.442^{**}	11.377^{**}	10.674^{**}

Table 5-1. Overall accessory usage (* p<0.10 ** p<0.05 *** p<0.01)

	N/A	None	Keyboard	Stylus pen	Both	Other	All Acc.
Cases	10	63	13	6	4	1	24
CGS_{Device}	20.20	18.57	15.23^{**}	21.50	22.75	18.00	18.17
CCS_{Device}	20.90	21.75	18.23^{**}	24.00	22.75	18.00	20.42
CGS	0.991^{**}	0.763	0.638	0.938	0.898	0.918	0.768
CCS	0.847	0.883	0.805	1.071	0.826	0.918	0.880
IPSI	8.778	9.007	7.148^{*}	11.751^{**}	10.167	8.266	8.849

Table 5-2. Smartphone accessory usage (* p<0.10 ** p<0.05 *** p<0.01)

	N/A	None	Keyboard	Stylus pen	Both	Other	All Acc.
Cases	12	28	21	11	7	5	44
CGS_{Device}	14.50^{***}	20.46	17.71^{*}	22.55	23.71	21.60	20.32
CCS_{Device}	16.92^{***}	22.68	19.05^{**}	24.18	25.29	21.20	21.57
CGS	0.869	1.001	0.942	0.910	0.977	0.962	0.942
CCS	0.923	0.962	0.890	0.945	1.019	0.772	0.911
IPSI	6.935^{***}	11.222	8.511^{***}	10.605	11.963	10.069	9.760^{**}

Table 5-3. Tablet computer accessory usage (* p<0.10 ** p<0.05 *** p<0.01)

	N/A	None	Keyboard	Stylus pen	Both	Other	All Acc.
Cases	8	17	41	2	3	9	60
CGS_{Device}	21.38	23.24	24.46	22.00	24.38	25.67	24.55
CCS_{Device}	20.88	23.35	24.90	22.00	24.88	25.89	24.95
CGS	0.988	1.002	1.077	1.042	0.939	0.993	1.044
CCS	0.951	0.902	0.984	1.000	0.902	0.953	0.969
IPSI	10.069	10.057	12.175^{**}	10.125	11.624	12.449^{**}	12.074^{***}

Table 5-4. Laptop computer accessory usage (* $p<0.10$ ** $p<0.05$ *** $p<0.01$)

These results show that overall, when employees used various accessories with their mobile devices, the CGS were higher, which leaded to higher IPSI. More specifically, the usage of accessories in general increased employees' perceptions about devices' information processing support capabilities related to job-required content-generation activities. The perceived device capabilities in performing content-consumption activities also increased slightly with the usage of accessories. However, as the device breakdown shows, increases in these scores were primarily driven by the laptop computer cases. Because the laptop computers have built-in keyboards, larger displays, and better processing power, their IPSI scores are the highest among all three types of devices.

In the cases of smartphones and tablet computers, usage of various accessories was generally associated with decreases in the perceived information processing support capabilities of these devices. One possible explanation is that employees adopted various accessories when these devices could not fulfill their needs to perform job-required information-processing activities. For example, if an employee wanted to be able to engage in extensive information-generation activities, such as creating and editing email, documents, and so on, s/he might find that using a smartphone or a tablet computer alone is not as convenient as using them with Bluetooth keyboards. Therefore, employees might adopt various accessories to aid their uses of these devices at work. Consequently, they may have lower perceptions about the devices' inherent capabilities to perform these tasks.

The IPSI scores were all perception-based measurements. Besides the devices' capabilities, other factors such as people's expectations, prior experiences, and levels of technical skills could also influence employees' perceptions about the devices' information processing support capabilities. The IPSI framework proposed in this research did not specify what factors influence employees' perceptions about various devices and how those factors might be related to the perceptions. Therefore, the current research only offers a tentative explanation about the decrease in perceived device capabilities when people are using various accessories with smartphone and tablet computers. A subsequent study is needed to explore these additional factors.

2.2. Usage experiences across different devices

In Chapter IV, the pilot studies showed that people have different usage experiences with the three types of devices. As summarized in Table 5-5, the main study data showed similar trends. Overall, the participants were most familiar with laptop computer, with the majority having more than two years of usage experience. The next one was the smartphone, which most of the participants had used for more than one year. Finally, tablet computers were just gaining popularity, with usage experience spreads out from less than one month to more than two years.

Time of usage	Less than 1 month	1 to 3 months	3 to 6 months	6 to 12 months	12 to 24 months	More than 24 months	Total responses
Smartphone	4	4	10	28	70	127	243
Tablet Computer	47	18	17	25	47	83	237
Laptop Computer	4	8	10	9	22	189	242

Table 5-5. Time of usage across devices

These results are consistent with current market development of these mobile computing devices. Although the infrastructure development in China (the number of wireless access points, quality of mobile networks, network connection speed, etc.) is lagging behind the U.S., the results showed that, in terms of the usage experience, device adoption patterns are similar. People were more familiar with laptop computers and smartphones, while tablet computers were still catching up.

As introduced in Chapter III, the common method variance (CMV) is a serious threat to the results of data analysis, especially when all the variables were captured using the same survey questionnaire. The current study conducts several post-hoc tests to mitigate the potential problems of CMV in the main study data analyses. The following section discusses these CMV related issues.

3. Common Method Variance Issues

As discussed by various scholars, one important threat to the validity of empirical results of data analysis is the presence of common method variance and biases. Common method variance refers to the variations in the data that comes from the method of data collection rather than the underlying constructs. TAM research has been criticized heavily for common method variances. Since the current study utilized paper-based survey questionnaires, common method variance and biases must be controlled. One of the best ways to control common method variance and biases is through better research design. However, other factors may constrain the available methods. Chapter III provided a brief discussion about the common method variance issue in this study. Generally, because this study is exploratory in nature, one of the primary goals is to develop and test the new IPSI scale. The Chinese university setting offered a great opportunity to gather extensive empirical data about multiple types of devices. However, due to the limitations of network access, language, and norms, paper-based survey questionnaires offered the most effective way to collect empirical support.

In order to assess the extent to which common method variance and biases influenced the results, several tests were conducted as suggested by Friedrich, et al. (2009). First, the Harman's Single Factor test was performed. This test involves performing an Exploratory Factor Analysis (EFA) using all measurement items and extracting only one factor. If the extracted factor accounts for more than half of the total variance, common method variance is present. Table 5-6 below shows the summary of this test.

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.755	42.984	42.984	13.755	42.984	42.984

Extraction Method: Principal Component Analysis.

Table 5-6. Harman's single factor test

The results indicate that the extracted factor accounts for 42.98% of the total variance, which is less than 50%. However, the results did show that a considerable proportion of the total variances were shared among all measurement models. Therefore, a common method latent factor analysis was performed to assess the magnitude of common variances. Table 5-7 summarizes the factor loadings with and without the common method latent variable in the structural model.

Item	With CMF	Without CMF	Difference	% Change
CGSD1	0.538	0.888	0.35	39.41
CGSD2	0.668	0.884	0.216	24.43
CGSD3	0.615	0.822	0.207	25.18
CGSD4	0.465	0.800	0.335	41.88
CCSD1	0.497	0.819	0.322	39.32
CCSD2	0.563	0.864	0.301	34.84
CCSD3	0.611	0.861	0.25	29.04
CCSD4	0.415	0.764	0.349	45.68
CGSJ1	0.477	0.820	0.343	41.83
CGSJ2	0.517	0.879	0.362	41.18
CGSJ3	0.413	0.747	0.334	44.71
CGSJ4	0.366	0.791	0.425	53.73

CCSJ1	0.375	0.803	0.428	53.30
CCSJ2	0.416	0.854	0.438	51.29
CCSJ3	0.418	0.836	0.418	50.00
CCSJ4	0.351	0.779	0.428	54.94
MCS1	0.389	0.613	0.224	36.54
MCS2	0.4	0.803	0.403	50.19
MCS3	0.402	0.803	0.401	49.94
MCD1	0.627	0.606	-0.021	-3.47
MCD2	0.773	0.795	0.022	2.77
MCD3	0.855	0.899	0.044	4.89
SI2	0.841	0.839	-0.002	-0.24
SI3	0.884	0.907	0.023	2.54
SI4	0.612	0.676	0.064	9.47
MCSE1	0.357	0.747	0.39	52.21
MCSE2	0.355	0.857	0.502	58.58
MCSE3	0.442	0.902	0.46	51.00
AI2	0.394	0.945	0.551	58.31
AI3	0.381	0.874	0.493	56.41

Table 5-7. Common method latent factor analysis

A structural equations modeling analysis incorporating the common method factor was performed to assess the effect of common method biases using SAS.

SAS			***Theory Based Model***		***Model with CMF***	
Paths Modeled:			*Parameter Coefficient*	*t-value*	*Parameter Coefficient*	*t-value*
IPSI	→	MCS	0.70**	18.11	0.82**	18.98
IPSI	→	MCD	-0.31**	-5.07	-0.28**	-4.40
IPSI	→	AI	0.02	0.25	-0.19	-1.21
MCS	→	AI	0.40**	5.59	0.54**	3.47
MCD	→	AI	0.12**	2.60	0.13**	2.54
SI	→	AI	-0.14**	-2.78	0.18**	3.14
MCSE	→	AI	0.67**	12.65	0.69**	10.53
Overall Fit:						
χ^2 (and d.f.)			320.68 (81)		909.14 (375)	
CFI			0.90		0.92	
RMSEA			0.11		0.073	

Table 5-8. SAS model estimations (* p<0.10 ** p<0.05 *** p<0.01)

Overall, these analyses showed that CMV was present in the data. However, the common method biases were not causing significant changes to the hypotheses testing results. After controlling for CMV, the data provided essentially the same hypotheses testing results.

4. Issues in Multiple Regression Analysis

As discussed in Chapter IV, the multiple regression analysis showed some interesting results. First, the IPSI and MCSE constructs both have positive associations with the mobile-computing-device-adoption intention (AI). Their standardized coefficients in both models revealed that although both relationships are statistically significant different from zero ($p<0.01$), MCSE had a much stronger impact on AI than IPSI did. In addition, although the social influence (SI) construct had a positive zero-order correlation with AI, its regression coefficient was negative. When MCS and MCD were added to the model, the negative regression coefficient of SI became statistically significant at $p<0.05$ level. The change in the statistical significance level indicated that there was some suppressing effect exists. When other variables were added into the model, they helped account for the variance that was not explained by the original regression. Therefore, the inclusion of these variables reduced the error variance, making the prior non-significant relationship significant (MacKinnon et al, 2007). However, the reversed sign of SI was interesting since it was to the opposite of the hypothesized relationship.

In order to analyze the reversed regression coefficients of SI, a series of separate regression analyses were performed, starting with a simple regression that only involves SI and AI. As the results showed, SI alone had a significant positive association with AI at $p<0.001$ level. When IPSI and MCS were added to the model, SI still had a significant positive association with AI at $p<0.01$ level. However, when MCD was introduced to the model, the positive association became insignificant and when MCSE was added, the regression coefficient of SI reversed and became significant again. The standardized regression coefficient of SI was decreasing as more variables were added to the model and was getting closer to zero. Table 5-9 shows the summary of these regression analyses.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.237[a]	.056	.052	1.2805295	.056	15.670	1	264	.000
2	.556[b]	.309	.304	1.0977906	.253	96.206	1	263	.000
3	.557[c]	.310	.302	1.0989918	.001	.425	1	262	.515
4	.674[d]	.455	.446	.9788376	.145	69.270	1	261	.000
5	.775[e]	.601	.594	.8385175	.147	95.662	1	260	.000

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4.575	.241		19.015	.000
	SI	.229	.058	.237	3.959	.000
2	(Constant)	2.847	.271		10.495	.000
	SI	.138	.051	.142	2.731	.007
	IPSI	.208	.021	.512	9.808	.000
3	(Constant)	2.986	.345		8.657	.000
	SI	.144	.052	.149	2.803	.005
	IPSI	.203	.022	.501	9.131	.000
	MCD	-.033	.051	-.035	-.652	.515
4	(Constant)	1.240	.372		3.334	.001
	SI	.051	.047	.053	1.085	.279
	IPSI	.090	.024	.222	3.754	.000
	MCD	.071	.047	.075	1.503	.134
	MCS	.563	.068	.518	8.323	.000
5	(Constant)	.808	.322		2.510	.013
	SI	**-.090**	**.043**	**-.093**	**-2.105**	**.036**
	IPSI	.060	.021	.146	2.855	.005
	MCD	.085	.040	.090	2.100	.037
	MCS	.280	.065	.258	4.329	.000
	MCSE	.546	.056	.541	9.781	.000

a. Dependent Variable: AI

Table 5-9. Summary of regression analyses about SI

According to the results, MCSE had a strong interaction with SI on its association with AI. This interaction suggested there might exist a moderating effect of MCSE on the relationship between SI and AI. To explore the possible moderation effect, a model was tested in which

MCSE acted as a moderator between SI and AI. As shown in Figure 5-1, the model was tested using SPSS macro PROCESS.

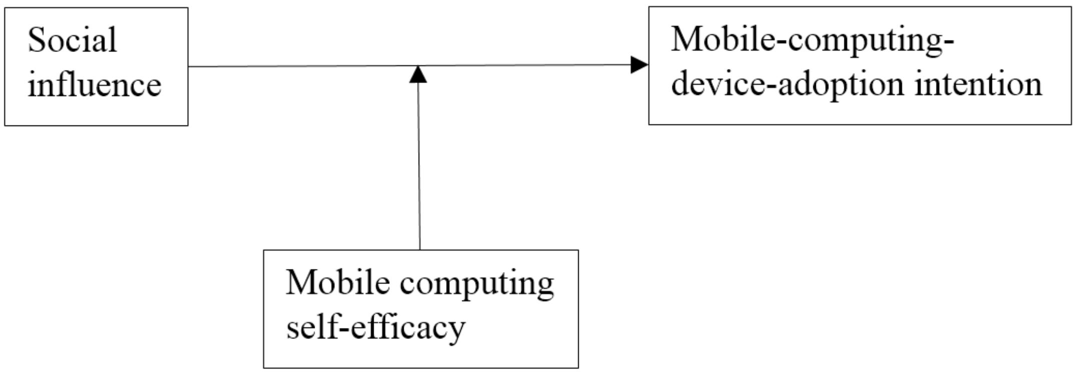


Figure 5-1. Suspected moderation effect of MCSE on SI → AI

The moderation analysis results are attached in Appendix D. The interaction term had a regression coefficient of 0.074 and is statistically significant at $p<0.05$ level ($p=0.012$) suggesting there is significant moderation effect of MCSE on the relationship between SI and AI. To demonstrate, Figure 5-2 below shows the conditional effect of SI on AI as a function of MCSE using Johnson-Neyman technique.

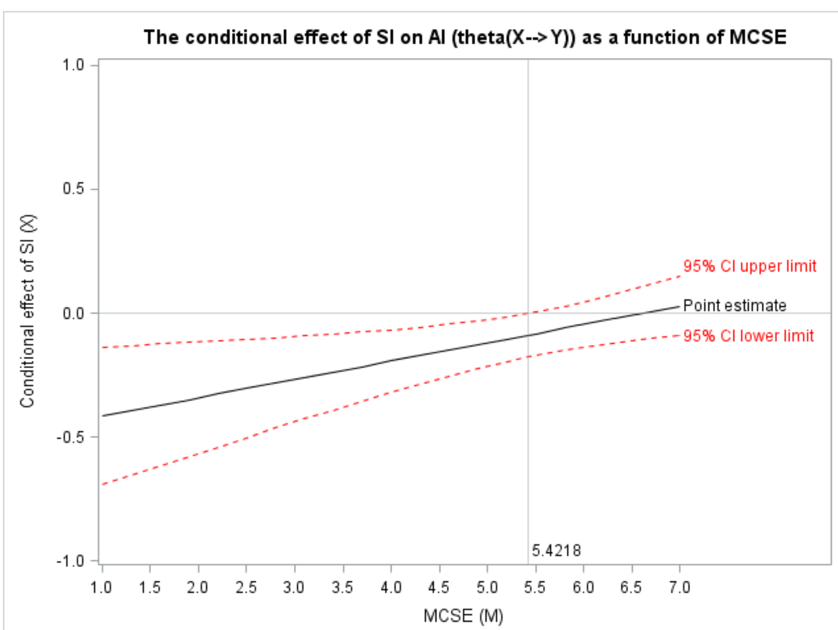


Figure 5-2. The moderation effect of MCSE on SI → AI

These results show that when MCSE was controlled for, SI had a negative association with AI. The negative effect of SI on AI was strongest when MCSE was at its minimum level. As MCSE increases, the negative effect of SI on AI decreases. When MCSE was above 5.4, the negative effect of SI on AI became statistically insignificant. In other words, when the employees' mobile computing self-efficacy is low, social influence negatively affects their device adoption intentions. When their MCSE is higher than 5.4, social influence will not significantly affect their device adoption intentions.

These results indicate that when people think the mobile computing devices have high influence on their social status and impressions, if they are not confident about using these devices, they will be less likely to adopt these devices. However, if they are very confident about their ability to use these devices, their adoption intentions will be less affected by their ideas about the social influences of these devices. Hypothesis 4 was not supported, but the suspected moderation model had some empirical support from the data. The relationships between MCSE, SI, and AI therefore need to be studied more in the future. The following section discusses the MCD construct, which had a similar reversal of sign in its regression coefficient.

5. Issues in Mediation Analysis

The two proposed mediators MCS and MCD were analyzed using both multiple regression and bootstrap-based mediation analyses. In the multiple regression results, IPSI had a significant positive association with AI when the two mediators were added into the model. The regression coefficient of IPSI also became smaller. MCS had a significant positive association with AI and MCD had an insignificant positive association with AI. These results suggest that MCS partially mediated the positive association between IPSI and AI, while MCD was not mediating the relationship between IPSI and AI, since MCD was not significantly related to AI.

Mediation analysis using the PROCESS macro demonstrated similar results: the indirect effect of MCS on AI was positive while the indirect effect of MCD on AI was negative. In these analyses, the effects IPSI had on MCD were negative and statistically significant while the effects MCD had on AI were positive and insignificant. The different signs of the effects indicated that the MCD was an inconsistent mediator. Overall, the data showed that higher IPSI scores did lead to lower levels of mobile computing dissatisfaction, but lowered MCD was not increasing employees' mobile-computing-device-adoption intentions.

These results are interesting. Intuitively, a lower MCD measure should lead to higher adoption intentions as predicted by the theory. One possible explanation for this result is that the data of AI were skewed toward higher adoption intentions. The mean score for AI is 5.47, which is the highest among all measurements. Therefore, the variability of AI is smaller than other measures. The mean score of MCD is 3.59, which is the smallest among all measurements. The MCD was coded in such a way that a higher score meant higher dissatisfaction. Therefore, these results show that overall, people are generally more likely to adopt these devices and less likely to be dissatisfied.

Another reason that MCD has a low mean score may be the delivery method of these surveys. The department chairs of each school distributed all survey questionnaires in the regular staff meetings. As a result, the participants may be not fully willing to express their dissatisfactions even though their responses were kept anonymous. Due to the limitation related to the institutional setting, the current study could not control for these influences. Therefore, a future study is needed to explore the relationships among IPSI, MCD, and AI.

6. Demographics controls

The current study collected various demographic data to explore the potential impact of these variables on the proposed relationships among constructs. Nonparametric independent tests were utilized to examine the distributions of the constructs in the model across age, gender, tenure, and department. The results showed that all constructs had similar distributions across gender and age. However, the distributions of SI were significantly different across different tenure groups. As Table 5-10 and Figure 5-3 shows, the mean scores of SI differ in each of the six tenure groups.

Tenure	<6m	6m-12m	1y-2y	3y-6y	7y-10y	11y+
Cases	10	11	43	70	62	68
SI mean score	3.7000	4.1818	4.5039**	3.8333	3.9731	3.5882

Table 5-10. Distribution of SI across tenure (** p<0.05)

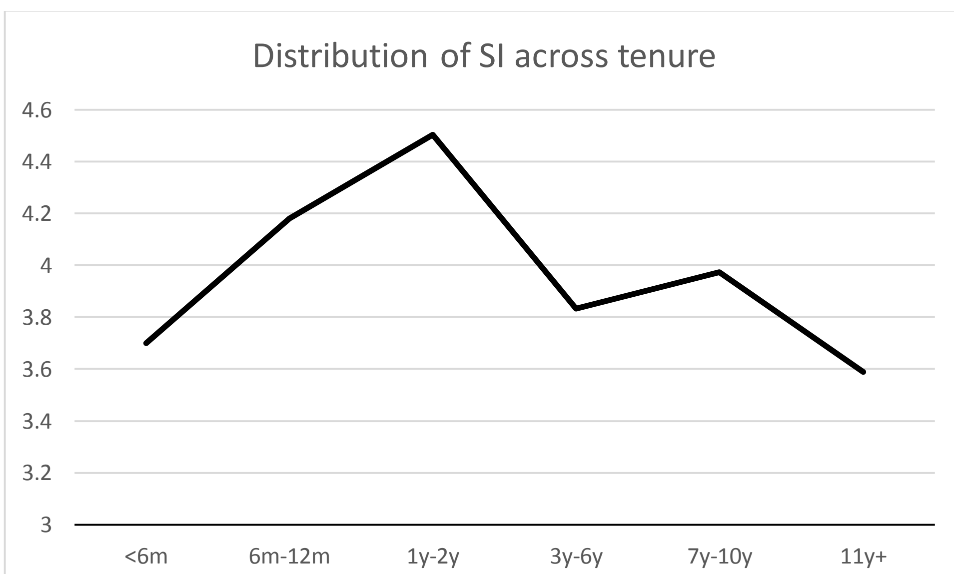
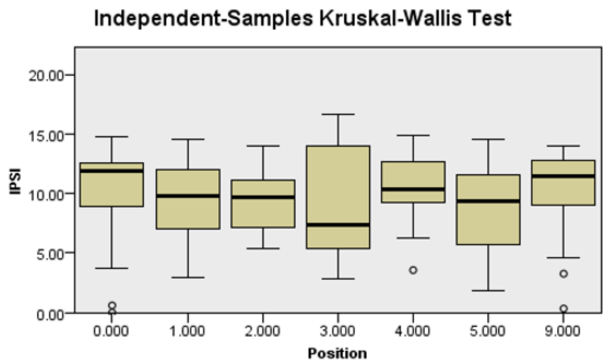


Figure 5-3. SI mean scores across tenure groups

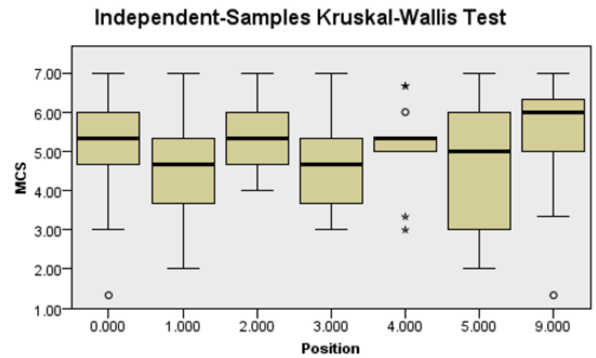
These results suggested that the employees who had been in the organization for one to two years have the highest SI mean score. Before that point, employees' average SI score was increasing and after that, the mean score of SI was decreasing. In other words, on average, employees who had been working in the Chinese university for one to two years thought mobile devices have the greatest social influence on their social status and impressions. The difference is significant at the $p<0.05$ level. This result is very interesting. It revealed that the mobile computing devices could serve as means through which people manage their social influences. The differences also indicated that employees in different stages of organization tenure view social influence differently. It is interesting that employees who have worked in an organization for one to two years have the highest SI mean score. According to the promotion schedule in the Chinese university, that period is the time during which employees are most likely to receive their first promotions. Therefore, the data suggested an interesting future research direction: how do employees in different tenure groups use mobile computing devices as tools to enhance their social influences?

When compared across the nine different departments, the results show that the distributions of IPSI, MCS, MCSE, and AI differ significantly. These results provided some additional support for the IPSI framework. The focus and expertise of the employees in these various departments are different from each other. For example, the school of computer science and the center of modern educations have different teaching and researching foci. Therefore, the frequency and importance of job-required information-processing activities are also likely to be different. The IPSI framework captured these differences, and therefore was different across these departments.



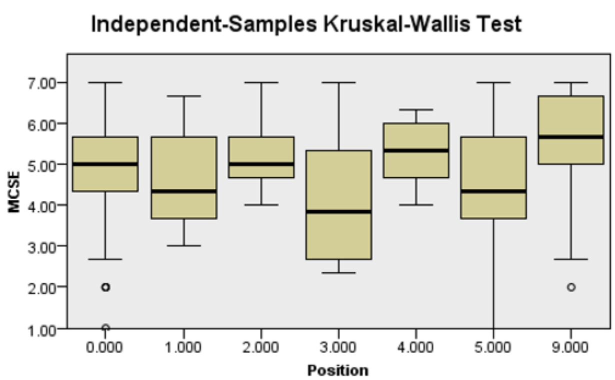
Total N	266
Test Statistic	13.073
Degrees of Freedom	6
Asymptotic Sig. (2-sided test)	.042

1. The test statistic is adjusted for ties.



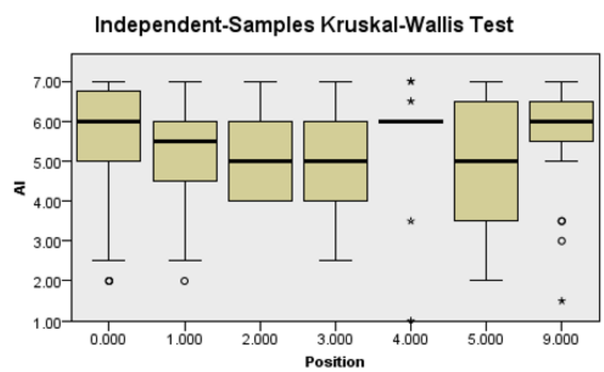
Total N	266
Test Statistic	26.124
Degrees of Freedom	6
Asymptotic Sig. (2-sided test)	.000

1. The test statistic is adjusted for ties.



Total N	266
Test Statistic	25.953
Degrees of Freedom	6
Asymptotic Sig. (2-sided test)	.000

1. The test statistic is adjusted for ties.



Total N	266
Test Statistic	13.188
Degrees of Freedom	6
Asymptotic Sig. (2-sided test)	.040

1. The test statistic is adjusted for ties.

Figure 5-4. Independent sample tests across departments

As shown in Figure 5-4, the different IPSI scores will lead to different levels of MCS across departments, as predicted by Hypothesis 2. In fact, the distribution of IPSI and MCS are similar across different departments. Since the nine different departments are in different disciplines, the levels of MCSE differ based on the various backgrounds of their employees. Finally, different IPSI, MCS, and MCSE will lead to different AI across departments as suggested by the model in the current study.

7. Chapter Summary

This chapter discusses various issues in the main data analysis. Overall, the proposed IPSI framework has some empirical support from both the pilot and main study data. Some factors that are unique to the Chinese university context influenced the IPSI scores. After a careful analysis of common method variance and biases, the hypotheses testing results still hold. Further analyses about social influence, mobile computing dissatisfaction, and organization tenure are needed. These future directions are discussed in Chapter VI.

The next Chapter discusses the major contributions and implementation of the current study. Several limitations and key assumptions are also discussed. Finally, Chapter VI concludes the study after discussing the future research directions.

CHAPTER VI

CONCLUSIONS

1. Chapter Overview

This chapter finishes this dissertation by first discussing conclusions from the conceptual model in light of the data analyses and hypotheses testing results. Next, the major contributions and implications of this study's findings are highlighted. Finally, after illustrating key assumptions and limitations, this chapter provides some future research directions.

2. Conclusions

This study examined two major research questions: "Why do employees choose to adopt different mobile computing devices at work?" and "What are the factors affecting employees' mobile-computing-device-adoption decisions?" Drawing primarily from the literature on the information-processing based view of firms, the dissertation first develops the Information Processing Support Index (IPSI) framework. The IPSI framework captures employees' perceptions about device capabilities and job requirements in terms of two types of information processing activities: content generation and content consumption.

This study examined three types of mobile computing devices: smartphones, tablet computers, and laptop computers. Based on the literature in scale development and the domain-sampling model (Nunnally and Bernstein, 1994), the current study conducted a Q-sort test, two pilot studies, and a main study in both the U.S. and China to generate, refine, and validate new measurement instruments for the IPSI framework. Overall, these instruments have demonstrated adequate levels of reliability, content validity, convergent validity, and discriminant validity.

Next, a conceptual model of employees' mobile-computing-device-adoption intentions in the workplace was proposed and empirically tested. The model utilizes IPSI, mobile computing satisfaction (MCS), mobile computing dissatisfaction (MCD), social influences (SI), and mobile computing self-efficacy (MCSE) to explain employees' mobile-computing-device-adoption intentions (AI) at work. Five hypotheses were tested using the empirical data.

The hypotheses testing results provided some empirical support for three of five proposed hypotheses in the mobile-computing-device-adoption intention model. The positive association between IPSI and AI (Hypothesis 1), the positive association between MCSE and AI (Hypothesis 5), and the mediating effect of MCS between IPSI and AI (Hypothesis 2) were empirically supported by the data. Table 6-1 summarizes the hypotheses testing results.

Hypotheses	**Supported?**
H1: The IPSI has a positive association with an employee's mobile-computing-device-adoption intention.	Yes
H2: Mobile-computing satisfaction mediates the positive relationship between the IPSI and an employee's mobile-computing-device-adoption intention.	Yes
H3: Mobile-computing dissatisfaction mediates the positive relationship between IPSI and an employee's mobile-computing-device-adoption intention.	No
H4: Social influence of mobile computing devices has a positive association with an employee's mobile computing-device-adoption intention.	No (Yes after controlling CMV)
H5: An employee's Mobile Computing Self-Efficacy (MCSE) has a positive association with their mobile-computing-device-adoption intention.	Yes

Table 6-1. Hypotheses testing results

The data analyses showed that IPSI had a negative association with MCD. However, the association between MCD and AI was positive. Therefore, because MCD was identified as an inconsistent mediator, the mediating effect of MCD between IPSI and AI (Hypothesis 3) was not supported. In other words, the data revealed that people who had higher IPSI tended to have lower MCD. On the other hand, people who had lower MCD generally showed lower AI after controlling for other factors in the model. Because these surveys were distributed at the employees' weekly staff meetings, there may exist some minor inconsistences in their responses to the MCD construct. The means of AI measurement were also skewed toward the higher end, indicating the majority of the participants had high levels of AI. In addition, based on comments collected from the participants, the majority of their feelings related to MCD stemmed from the infrastructure limitations such as slow wireless network speed, limited Wi-Fi coverage, and others. Therefore, the positive effect of MCD on AI could be caused by its interactions with these facts.

The data analyses also revealed that there was a negative association between SI and AI after controlling for other factors in the model. Therefore, Hypothesis 4 was not supported. The fact that the relationship between SI and AI was contrary to the model prediction is very interesting. Further analysis showed that MCSE had a strong interaction with SI. In addition, the distribution of SI was different across tenure groups, in which employees who had one to two years of tenure rated highest on SI. As a result, the negative associations between SI and AI were possibly a result of the suppressing effect of MCSE.

3. Contributions and Implications

This study made several theoretical and practical contributions. First, the information processing support index (IPSI) provides a new and more relevant perspective to examine information systems adoption behavior at the individual employee level. When studying information systems adoptions intentions, the technology acceptance model (TAM) is dominant in the MIS field. However, as discussed early in this study, although TAM was developed, refined, and validated rigorously over time, it provides relatively limited practical value. The perceived usefulness (PU) and perceived ease of use (PEU) constructs are abstract in nature and ignore other potentially important factors (Bagozzi, 2007; Benbasat and Barki, 2007). The IPSI framework developed in this study suggests that information systems adoption behavior can be explored from the basic functions of these systems (information processing) and the job requirements of these functions. It also provides a quantifiable measure for two types of information processing activities. Although the context of this study is limited to mobile computing devices, the IPSI framework can be extended to more general information systems adoption behaviors.

Second, this study develops and validates new measurement instruments for the IPSI framework. These instruments provide valid and reliable measures of the IPSI sub-scores. The four sub-scores (CGS_{Device}, CCS_{Device}, CGS_{Job}, CCS_{Job}) are indicators of employees' perceptions about both device capabilities and job requirements in content generation and consumption related tasks. The fact that these measurements are perception-based ensures that they are independent of the rapid development of technology.

Third, from a more practical perspective the IPSI framework provides a starting point to develop quantifiable measures to evaluate different device options organizations can offer to their employees. This can be useful to help organizations manage these devices at work more effectively. It will also contribute to the understanding of the current bring your own device (BYOD) trend in industries. One potential reason that employees want to bring their own mobile computing devices to work, especially tablet computers, is that they believe these devices can help them get their work done more efficiently. In other words, mobile computing devices can better support employees' perceived information processing needs. This study provided some empirical support for that argument.

Finally, the insights gathered from these information-processing perspectives can guide the mobile computing industry to design and develop new technologies that are focused on improving the information processing support needed at work. For example, as the computational capability of mobile devices increases, employees facing those computational intensive information-processing tasks will be more likely to adopt devices that can better support those activities.

4. Assumptions and Limitations

The current study is exploratory in nature. Therefore, several assumptions about the model and limitations need to be highlighted. Readers should keep these limitations and assumptions in mind when interpreting the results.

First, this study focuses on examining employees' mobile computing device adoptions in academic institutions. All of the participants are from higher education. The sample in the main study contains faculty and staff member from one public university in China. Although the survey instruments were distributed across several departments, this is not a complete randomized sample across different organizations or industries. Therefore, the results of hypotheses testing have limited generalizability to other industries and situations. However, given that the first goal of this study was to develop and validate new measurement instruments, this sample was adequate for that purpose.

Second, the main study utilized paper-based survey instruments to collect all measurements in the model, which may cause some common method bias problems. As discussed in Chapter V, given the general goals of this study, versus these limitations, the paper-based survey were a satisfactory means to collect the main study data. Common latent factor analysis and structural equations path analysis revealed that although common method variance was present in the data, it only had very small effects on the results. Therefore, the common method variance was not a major source of problems in the data analyses.

Third, the design of this study is cross-sectional. The proposed hypotheses were all concerned about the "associations" between independent and dependent variables rather than causal relationships. Cross-sectional data have limited ability to infer causality. As a result, the directions of the proposed effects can only be established based on previous literature. Some of the relationships, such as the negative association between social influence and mobile-computing-device-adoption intentions need further analysis.

Finally, all of the participants are from China. They have different cultural backgrounds and norms than people in the U.S. In addition, as mentioned earlier, the infrastructure development status (wireless connectivity, network speed, etc.) in China is also different from other places. Therefore, the results of the current study can only be generalized to a limited context. These differences may have influenced the results in this study.

5. Future Research Directions

Based on the discussions above, several future research directions are suggested. First, the information processing support index (IPSI) framework developed in this study needs to be cross-validated with data from other industries. In the current study, only the usage of mobile computing devices in higher education was examined. In order to establish the generalizablity of the IPSI framework, future studies need to apply it to a wider range of different industries such as healthcare, sales, financial services, etc. Different industries may require different levels of job-related information processing activities. The IPSI framework will capture these differences in its job-related measures. Therefore, a cross industry comparison about job-required information processing can be made to improve our understanding about mobile computing device adoption behaviors in different areas.

Second, as discussed in earlier sections, this dissertation focused on using IPSI to examine individual-level mobile computing device adoptions. Future research should extend the context to more general types of information systems and different levels. Since information processing is the most basic functions of information systems, the IPSI framework can be used to explore more general information system adoptions, including adoption intentions related to multiple device users and different user groups.

Third, since the main study participants in this study were from one large public university in China, studies are needed to collect more information in the U.S. and compare the differences. The comparison can reveal important factors affecting mobile computing device adoption behaviors across different cultures. For example, social influences may have different effects on employees' mobile device adoption intentions due to cultural differences.

Finally, as discussed in Chapter V, this new model of employees' mobile-computing-device-adoption intentions is exploratory. Therefore, it is very important for future studies to advance the model by incorporating additional factors and potential moderators. For example, social influence and mobile computing self-efficacy in the current study showed some interesting effects that need to be further examined. In theory development, the moderators are important since they specify the boundary conditions of proposed effects. As a result, more studies are needed to develop the model further.

Mobile computing device adoptions are growing rapidly. This study provides an important and useful perspective to examine systematically why and how employees choose to adopt different mobile computing devices at work. Based on an information processing perspective, the newly developed Information Processing Support Index framework and mobile-computing-device-adoption intentions model provide some useful insights about this new development in mobile computing and in general information system adoption behaviors.

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LIST OF APPENDICES

APPENDIX A. PILOT SURVEY INSTRUMENT LIST

Please indicate the degree to which you agree with the following statements:

CGS$_{Device}$:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CGSD1	The [mobile device][1] is capable of performing tasks related to creating/editing email and other messages.	☐	☐	☐	☐	☐	☐	☐
CGSD2	The [mobile device] is capable of performing tasks related to creating/editing work-related documents.	☐	☐	☐	☐	☐	☐	☐
CGSD3	The [mobile device] is capable of performing tasks related to creating/editing content on social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CGSD4	The [mobile device] is capable of performing content-generation-related tasks at work.	☐	☐	☐	☐	☐	☐	☐

CCS$_{Device}$:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CCSD1	The [mobile device] is capable of performing tasks related to reading email and other messages.	☐	☐	☐	☐	☐	☐	☐
CCSD2	The [mobile device] is capable of performing tasks related to reading work-related documents.	☐	☐	☐	☐	☐	☐	☐
CCSD3	The [mobile device] is capable of performing tasks related to reading content on social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CCSD4	The [mobile device] is capable of performing content-consumption-related tasks at work.	☐	☐	☐	☐	☐	☐	☐

[1] In this study, there are three types of mobile computing devices: smartphones, tablet computers, and laptop computers. In the actual survey questionnaire, the term mobile device will be replaced using one of the three devices.

CGS$_{Job}$:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CGSJ1	My job frequently requires me to create/edit email and other messages.	☐	☐	☐	☐	☐	☐	☐
CGSJ2	My job frequently requires me to create/edit work-related documents.	☐	☐	☐	☐	☐	☐	☐
CGSJ3	My job frequently requires me to create/edit content on social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CGSJ4	My job frequently requires me to engage in content-generation-related tasks.	☐	☐	☐	☐	☐	☐	☐

CCS$_{Job}$:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CCSJ1	My job frequently requires me to read email and other messages.	☐	☐	☐	☐	☐	☐	☐
CCSJ2	My job frequently requires me to read work-related documents.	☐	☐	☐	☐	☐	☐	☐
CCSJ3	My job frequently requires me to read content on social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CCSJ4	My job frequently requires me to engage in content-consumption-related tasks.	☐	☐	☐	☐	☐	☐	☐

Weights of CGS and CCS:

Please indicate the relevant importance of the following tasks in your job:

		Extremely Unimportant 1	2	3	4	5	6	Extremely Important 7
W1	Content-generation-related tasks (e.g., creating/editing email and other messages, work-related documents, and content on social network and other web pages)	☐	☐	☐	☐	☐	☐	☐
W2	Content-consumption-related tasks (e.g., reading email and other messages, work-related documents, and content on social network and other web pages)	☐	☐	☐	☐	☐	☐	☐

Mobile-Computing Satisfaction:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCS1	Overall, I feel satisfied with my mobile-computing needs in my organization.	☐	☐	☐	☐	☐	☐	☐
MCS2	My organization supports the usage of the [mobile device].	☐	☐	☐	☐	☐	☐	☐
MCS3	I feel satisfied with using the [mobile device] for performing my job.	☐	☐	☐	☐	☐	☐	☐

Mobile-Computing Dissatisfaction:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCD1	Overall, I feel dissatisfied with using mobile computing devices in my organization.	☐	☐	☐	☐	☐	☐	☐
MCD2	My organization does not support the usage of the [mobile device].	☐	☐	☐	☐	☐	☐	☐
MCD3	I feel dissatisfied with using the [mobile device] for performing my job.	☐	☐	☐	☐	☐	☐	☐

Social Influence:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
SI1	A large portion of my coworker(s) and my supervisor(s) are using the [mobile device].	☐	☐	☐	☐	☐	☐	☐
SI2	Using the [mobile device] is a status symbol in my organization.	☐	☐	☐	☐	☐	☐	☐
SI3	People will have a better impression of me if I am using the [mobile device].	☐	☐	☐	☐	☐	☐	☐
SI4	The [mobile device] is able to help me managing my impressions upon others.	☐	☐	☐	☐	☐	☐	☐

Mobile Computing Self-Efficacy:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCSE1	I feel confident about using the [mobile device] in my job.	☐	☐	☐	☐	☐	☐	☐
MCSE2	I feel confident about using most of the applications on the [mobile device].	☐	☐	☐	☐	☐	☐	☐
MCSE3	I feel confident about using the [mobile device) to get information I need.	☐	☐	☐	☐	☐	☐	☐
MCSE4	I feel confident in fixing problems about the [mobile device].	☐	☐	☐	☐	☐	☐	☐

Mobile-Computing-Device-Adoption Intentions

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCDAI1	I am willing to bring the [mobile device] to, and use it for, work.	☐	☐	☐	☐	☐	☐	☐
MCDAI2	Assume I am allowed to use the [mobile device], I intend to use it for work.	☐	☐	☐	☐	☐	☐	☐
MCDAI3	Given that I am allowed to use the [mobile device], I intend to use it for work.	☐	☐	☐	☐	☐	☐	☐

Demographic Information:
Please indicate the experience you have with the following mobile devices:

	Less than 1 month	1 to 3 months	3 to 6months	6 to 12 months	12 to 24 months
Smartphone	☐	☐	☐	☐	☐
Tablet computer	☐	☐	☐	☐	☐
Laptop computer	☐	☐	☐	☐	☐

Gender: ☐Male ☐Female

Age:
☐18-22 years old
☐23-30 years old
☐31-54 years old
☐55-64 years old
☐65 years or older

Major: What is your major?

APPENDIX B. REVISED SURVEY INSTRUMENT LIST

Please indicate the degree to which you agree with the following statements:

CGS$_{Device}$:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CGSD1	Without any accessories, the [mobile device][2] is capable of performing tasks related to creating/editing email and other messages.	☐	☐	☐	☐	☐	☐	☐
CGSD2	Without any accessories, the [mobile device] is capable of performing tasks related to creating/editing work-related documents.	☐	☐	☐	☐	☐	☐	☐
CGSD3	Without any accessories, the [mobile device] is capable of performing tasks related to creating/editing content on professional social network and other web sites.	☐	☐	☐	☐	☐	☐	☐
CGSD4	Without any accessories, the [mobile device] is capable of performing tasks that generate content for others at work.	☐	☐	☐	☐	☐	☐	☐

CCS$_{Device}$:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CCSD1	Without any accessories, the [mobile device] is capable of performing tasks related to reading email and other messages.	☐	☐	☐	☐	☐	☐	☐
CCSD2	Without any accessories, the [mobile device] is capable of performing tasks related to reading work-related documents.	☐	☐	☐	☐	☐	☐	☐
CCSD3	Without any accessories, the [mobile device] is capable of performing tasks related to reading content on professional social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CCSD4	Without any accessories, the [mobile device] is capable of performing tasks that require consuming content from others at work.	☐	☐	☐	☐	☐	☐	☐

[2] In this study, there are three types of mobile computing devices: smartphones, tablet computers, and laptop computers. In the actual survey, the term mobile device will be replaced using one of the three devices.

CGS_{Job}:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CGSJ1	My job frequently requires me to create/edit email and other messages.	☐	☐	☐	☐	☐	☐	☐
CGSJ2	My job frequently requires me to create/edit work-related documents.	☐	☐	☐	☐	☐	☐	☐
CGSJ3	My job frequently requires me to create/edit content on social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CGSJ4	My job frequently requires me to engage in tasks that generate content for others.	☐	☐	☐	☐	☐	☐	☐

CCS_{Job}:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
CCSJ1	My job frequently requires me to read email and other messages.	☐	☐	☐	☐	☐	☐	☐
CCSJ2	My job frequently requires me to read work-related documents.	☐	☐	☐	☐	☐	☐	☐
CCSJ3	My job frequently requires me to read content on social network and other web pages.	☐	☐	☐	☐	☐	☐	☐
CCSJ4	My job frequently requires me to engage in tasks that consume content from others.	☐	☐	☐	☐	☐	☐	☐

Weights of CGS and CCS:

Please indicate the relevant importance of the following tasks in your job:

		Extremely Unimportant 1	2	3	4	5	6	Extremely Important 7
W_{cgs}	Content-generation-related tasks (e.g., creating/editing email and other messages, work-related documents, and content on professional social network and other web pages)	☐	☐	☐	☐	☐	☐	☐
W_{ccs}	Content-consumption-related tasks (e.g., reading email and other messages, work-related documents, and content on professional social network and other web pages)	☐	☐	☐	☐	☐	☐	☐

Mobile-Computing Satisfaction:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCS1	Overall, I feel satisfied with my mobile-computing needs in my organization.	☐	☐	☐	☐	☐	☐	☐
MCS2	The [mobile device] makes it easier for me to complete my job.	☐	☐	☐	☐	☐	☐	☐
MCS3	I feel satisfied with using the [mobile device] for performing my job.	☐	☐	☐	☐	☐	☐	☐

Mobile-Computing Dissatisfaction:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCD1	Overall, I feel dissatisfied with using mobile computing devices in my organization.	☐	☐	☐	☐	☐	☐	☐
MCD2	The [mobile device] does not make it easier for me to complete my job.	☐	☐	☐	☐	☐	☐	☐
MCD3	I feel dissatisfied with using the [mobile device] for performing my job.	☐	☐	☐	☐	☐	☐	☐

Social Influence:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
SI1	Using the [mobile device] is a status symbol in my organization.	☐	☐	☐	☐	☐	☐	☐
SI2	People will have a better impression of me if I am using the [mobile device].	☐	☐	☐	☐	☐	☐	☐
SI3	The [mobile device] is able to help me managing my impressions upon others.	☐	☐	☐	☐	☐	☐	☐

Mobile Computing Self-Efficacy:

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCSE1	I feel confident about using the [mobile device] in my job.	☐	☐	☐	☐	☐	☐	☐
MCSE2	I feel confident about using most of the applications on the [mobile device].	☐	☐	☐	☐	☐	☐	☐
MCSE3	I feel confident about using the [mobile device) to get information I need.	☐	☐	☐	☐	☐	☐	☐

Mobile-Computing-Device-Adoption Intentions

		Strongly Disagree 1	2	3	4	5	6	Strongly Agree 7
MCDAI1	I am willing to bring the [mobile device] to, and use it for, work.	☐	☐	☐	☐	☐	☐	☐
MCDAI2	Assume I am allowed to use the [mobile device], I intend to use it for work.	☐	☐	☐	☐	☐	☐	☐
MCDAI3	Given that I am allowed to use the [mobile device], I intend to use it for work.	☐	☐	☐	☐	☐	☐	☐

Demographic Information:

Gender: ☐Male ☐Female

Age:
☐18-24 years old
☐25-34 years old
☐35-44 years old
☐45-54 years old
☐55-64 years old
☐65 years or older

Organization Tenure:
☐Less than 6 months
☐6 to 12 months
☐1 to 2 years
☐3 to 6 years
☐7 to 10 years
☐11 years or more

Education:
What is the highest level of education you have completed?
☐High school diploma or equivalent
☐Associate degree or certificate
☐Bachelor's degree
☐Master's degree
☐Doctoral degree
☐Professional degree (MD, JD, Etc.)

APPENDIX C. PILOT STUDY SPSS OUTPUT

1, Multiple regression analysis:

Descriptive Statistics

	Mean	Std. Deviation	N
AI	5.7363	1.14779	182
IPSI	13.0587	2.67119	182
SI	4.3489	1.20621	182
MCSE	5.6085	.93222	182
MCS	5.7344	1.04046	182
MCD	2.5696	1.34150	182

Correlations

		AI	IPSI	SI	MCSE	MCS	MCD
Pearson Correlation	AI	1.000	.308	.303	.644	.585	-.527
	IPSI	.308	1.000	.122	.274	.372	-.315
	SI	.303	.122	1.000	.385	.360	-.335
	MCSE	.644	.274	.385	1.000	.615	-.543
	MCS	.585	.372	.360	.615	1.000	-.740
	MCD	-.527	-.315	-.335	-.543	-.740	1.000
Sig. (1-tailed)	AI	.	.000	.000	.000	.000	.000
	IPSI	.000	.	.051	.000	.000	.000
	SI	.000	.051	.	.000	.000	.000
	MCSE	.000	.000	.000	.	.000	.000
	MCS	.000	.000	.000	.000	.	.000
	MCD	.000	.000	.000	.000	.000	.
N	AI	182	182	182	182	182	182
	IPSI	182	182	182	182	182	182
	SI	182	182	182	182	182	182
	MCSE	182	182	182	182	182	182
	MCS	182	182	182	182	182	182
	MCD	182	182	182	182	182	182

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	MCSE, IPSI, SI[b]	.	Enter
2	MCD, MCS[b]	.	Enter

a. Dependent Variable: AI

b. All requested variables entered.

Model Summary[c]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.661[a]	.437	.427	.86847	.437	46.050	3	178	.000	
2	.696[b]	.484	.469	.83603	.047	8.039	2	176	.000	.760

a. Predictors: (Constant), MCSE, IPSI, SI

b. Predictors: (Constant), MCSE, IPSI, SI, MCD, MCS

c. Dependent Variable: AI

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	104.198	3	34.733	46.050	.000[b]
	Residual	134.253	178	.754		
	Total	238.452	181			
2	Regression	115.436	5	23.087	33.031	.000[c]
	Residual	123.016	176	.699		
	Total	238.452	181			

a. Dependent Variable: AI

b. Predictors: (Constant), MCSE, IPSI, SI

c. Predictors: (Constant), MCSE, IPSI, SI, MCD, MCS

Coefficients[a]

Model		Unstandardized Coefficients: B	Unstandardized Coefficients: Std. Error	Standardized Coefficients: Beta	t	Sig.	Collinearity Statistics: Tolerance	Collinearity Statistics: VIF
1	(Constant)	.673	.458		1.470	.143		
	IPSI	.060	.025	.141	2.406	.017	.924	1.082
	SI	.058	.058	.061	1.003	.317	.851	1.175
	MCSE	.717	.077	.582	9.254	.000	.799	1.251
2	(Constant)	1.240	.760		1.632	.104		
	IPSI	.033	.025	.077	1.316	.190	.855	1.170
	SI	.016	.057	.016	.274	.784	.821	1.217
	MCSE	.532	.088	.432	6.058	.000	.577	1.734
	MCS	.221	.098	.200	2.253	.025	.372	2.688
	MCD	-.098	.070	-.114	-1.395	.165	.436	2.293

a. Dependent Variable: AI

CollinearityDiagnostics[a]

Model	Dimension	Eigenvalue	Condition	Variance Proportions

			Index	(Constant)	IPSI	SI	MCSE	MCS	MCD
1	1	3.912	1.000	.00	.00	.00	.00		
	2	.052	8.660	.02	.19	.78	.00		
	3	.023	13.129	.12	.74	.20	.31		
	4	.013	17.414	.86	.06	.01	.69		
2	1	5.650	1.000	.00	.00	.00	.00	.00	.00
	2	.258	4.679	.00	.00	.01	.00	.00	.29
	3	.051	10.477	.00	.16	.79	.00	.01	.01
	4	.025	15.101	.01	.76	.19	.13	.06	.00
	5	.011	23.144	.03	.05	.00	.81	.43	.00
	6	.005	33.491	.96	.03	.01	.06	.50	.69

a. Dependent Variable: AI

2, Mediation analysis using PROCESS Procedure by Hayes (2013):

```
Mediation Analysis:
Process by Andrew Hayes
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Release 2.10 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
Model = 4
    Y = AI
    X = IPSI
   M1 = MCS
   M2 = MCD

Sample size
        182
**************************************************************************
Outcome: MCS

Model Summary
          R       R-sq          F        df1        df2          p
      .3716      .1381    28.8411     1.0000   180.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8442      .3592    10.7015      .0000     3.1354     4.5530
IPSI          .1447      .0270     5.3704      .0000      .0916      .1979

**************************************************************************
Outcome: MCD

Model Summary
```

```
          R       R-sq          F        df1        df2          p
      .3154      .0995    19.8822     1.0000   180.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.6380      .4734     9.7967      .0000     3.7038     5.5721
IPSI         -.1584      .0355    -4.4590      .0000     -.2285     -.0883

**************************************************************************
Outcome: AI

Model Summary
          R       R-sq          F        df1        df2          p
      .6076      .3692    34.7282     3.0000   178.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0972      .7609     4.0705      .0001     1.5956     4.5987
MCS           .4429      .1000     4.4296      .0000      .2456      .6402
MCD          -.1706      .0759    -2.2484      .0258     -.3203     -.0209
IPSI          .0412      .0276     1.4913      .1377     -.0133      .0957

******************** DIRECT AND INDIRECT EFFECTS *************************

Effect         SE          t          p       LLCI       ULCI
      .0412      .0276     1.4913      .1377     -.0133      .0957

Indirect effect of X on Y
            Effect    Boot SE   BootLLCI   BootULCI
TOTAL      .0911      .0204      .0560      .1364
MCS        .0641      .0212      .0271      .1105
MCD        .0270      .0154      .0063      .0675

******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
     1000

Level of confidence for all confidence intervals in output:
    95.00

------ END MATRIX -----
```

Direct effect: .0412

Indirect effect: .0911

The ratio of indirect to direct effect (.0911/.0412 = 2.21) and the proportion of the total effect due to the indirect effect (.0911/.1323=.6886)

```
Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Release 2.10 ****************
```

```
          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
Model = 4
    Y = AI
    X = IPSI
   M1 = MCS
   M2 = MCD

Sample size
        182

**************************************************************************
Outcome: MCS

Model Summary
          R       R-sq          F        df1        df2          p
      .3716      .1381    28.8411     1.0000   180.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.8442      .3592    10.7015      .0000     3.1354     4.5530
IPSI          .1447      .0270     5.3704      .0000      .0916      .1979

**************************************************************************
Outcome: MCD

Model Summary
          R       R-sq          F        df1        df2          p
      .3154      .0995    19.8822     1.0000   180.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     4.6380      .4734     9.7967      .0000     3.7038     5.5721
IPSI         -.1584      .0355    -4.4590      .0000     -.2285     -.0883

**************************************************************************
Outcome: AI

Model Summary
          R       R-sq          F        df1        df2          p
      .6076      .3692    34.7282     3.0000   178.0000      .0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3.0972      .7609     4.0705      .0001     1.5956     4.5987
MCS           .4429      .1000     4.4296      .0000      .2456      .6402
MCD          -.1706      .0759    -2.2484      .0258     -.3203     -.0209
IPSI          .0412      .0276     1.4913      .1377     -.0133      .0957

******************** DIRECT AND INDIRECT EFFECTS *************************

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .0412      .0276     1.4913      .1377     -.0133      .0957
```

Indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.0911	.0200	.0573	.1360
MCS	.0641	.0203	.0289	.1103
MCD	.0270	.0155	.0056	.0679

Partially standardized indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.0794	.0150	.0526	.1105
MCS	.0559	.0167	.0253	.0911
MCD	.0235	.0131	.0049	.0563

Completely standardized indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.2121	.0428	.1347	.3024
MCS	.1492	.0463	.0673	.2513
MCD	.0629	.0350	.0126	.1514

Ratio of indirect to total effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.6888	.2197	.4331	1.2852
MCS	.4846	.1793	.2282	.9571
MCD	.2042	.1439	.0376	.6230

Ratio of indirect to direct effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	2.2132	88.1543	-3.1700	81.4636
MCS	1.5570	61.8771	-1.2351	55.6463
MCD	.6562	33.3592	-1.2792	25.7859

Normal theory tests for specific indirect effects

	Effect	se	Z	p
MCS	.0641	.0190	3.3824	.0007
MCD	.0270	.0137	1.9686	.0490

******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
5000

Level of confidence for all confidence intervals in output:
95.00

------ END MATRIX -----

APPENDIX D. MAIN STUDY SPSS OUTPUT

1. Multiple regression analysis:

Regression

Descriptive Statistics

	Mean	Std. Deviation	N
AI	5.475564	1.3154971	266
IPSI	10.039269	3.2378563	266
SI	3.924812	1.3574032	266
MCSE	4.926065	1.3027810	266
MCS	5.107769	1.2097084	266
MCD	3.587719	1.4061976	266

Correlations

		AI	IPSI	SI	MCSE	MCS	MCD
Pearson Correlation	AI	1.000	.538	.237	.725	.646	-.154
	IPSI	.538	1.000	.184	.500	.631	-.274
	SI	.237	.184	1.000	.416	.257	.128
	MCSE	.725	.500	.416	1.000	.648	-.194
	MCS	.646	.631	.257	.648	1.000	-.338
	MCD	-.154	-.274	.128	-.194	-.338	1.000
Sig. (1-tailed)	AI	.	.000	.000	.000	.000	.006
	IPSI	.000	.	.001	.000	.000	.000
	SI	.000	.001	.	.000	.000	.019
	MCSE	.000	.000	.000	.	.000	.001
	MCS	.000	.000	.000	.000	.	.000
	MCD	.006	.000	.019	.001	.000	.
N	AI	266	266	266	266	266	266
	IPSI	266	266	266	266	266	266
	SI	266	266	266	266	266	266
	MCSE	266	266	266	266	266	266
	MCS	266	266	266	266	266	266
	MCD	266	266	266	266	266	266

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	MCSE, SI, IPSI[b]	.	Enter
2	MCD, MCS[b]	.	Enter

a. Dependent Variable: AI
b. All requested variables entered.

Model Summary

					Change Statistics				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change
1	.755[a]	.571	.566	.8670056	.571	116.024	3	262	.000
2	.775[b]	.601	.594	.8385174	.031	10.053	2	260	.000

a. Predictors: (Constant), MCSE, SI, IPSI
b. Predictors: (Constant), MCSE, SI, IPSI, MCD, MCS

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	261.646	3	87.215	116.024	.000[b]
	Residual	196.945	262	.752		
	Total	458.591	265			
2	Regression	275.782	5	55.156	78.446	.000[c]
	Residual	182.809	260	.703		

Total		458.591	265			

a. Dependent Variable: AI
b. Predictors: (Constant), MCSE, SI, IPSI
c. Predictors: (Constant), MCSE, SI, IPSI, MCD, MCS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Correlations			Collinearity Statistics	
		B	Std. Error	Beta			Zero-order	Partial	Part	Tolerance	VIF
1	(Constant)	1.627	.235		6.924	.000					
	IPSI	.094	.019	.231	4.943	.000	.538	.292	.200	.749	1.335
	SI	-.070	.043	-.072	-1.614	.108	.237	-.099	-.065	.826	1.211
	MCSE	.645	.051	.639	12.635	.000	.725	.615	.512	.641	1.560
2	(Constant)	.808	.322		2.510	.013					
	IPSI	.060	.021	.146	2.855	.005	.538	.174	.112	.583	1.716
	SI	-.090	.043	-.093	-2.105	.036	.237	-.129	-.082	.779	1.283
	MCSE	.546	.056	.541	9.781	.000	.725	.519	.383	.501	1.996
	MCS	.280	.065	.258	4.328	.000	.646	.259	.169	.433	2.311
	MCD	.085	.040	.090	2.100	.037	-.154	.129	.082	.828	1.208

a. Dependent Variable: AI

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics		
						Tolerance	VIF	Minimum Tolerance
1	MCS	.230[b]	3.936	.000	.237	.455	2.198	.455
	MCD	.049[b]	1.132	.259	.070	.871	1.148	.626

a. Dependent Variable: AI
b. Predictors in the Model: (Constant), MCSE, SI, IPSI

Collinearity Diagnostics[a]

Model	Dimension	Eigenvalue	Condition Index	Variance Proportions					
				(Constant)	IPSI	SI	MCSE	MCS	MCD
1	1	3.845	1.000	.00	.00	.01	.00		
	2	.083	6.819	.00	.34	.63	.00		
	3	.041	9.680	.73	.46	.29	.01		
	4	.031	11.157	.27	.20	.08	.98		
2	1	5.667	1.000	.00	.00	.00	.00	.00	.00
	2	.178	5.636	.00	.05	.00	.01	.01	.43
	3	.078	8.520	.01	.09	.80	.00	.01	.09
	4	.037	12.373	.05	.76	.15	.22	.05	.04
	5	.024	15.398	.44	.03	.05	.61	.06	.24
	6	.015	19.258	.49	.07	.00	.16	.88	.21

a. Dependent Variable: AI

2. Mediation Analysis using PROCESS

```
***************** PROCESS Procedure for SPSS Release 2.10 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
```

```
Model = 4
    Y = AI
    X = IPSI
   M1 = MCS
   M2 = MCD
Sample size
        266
**************************************************************************
Outcome: MCS
Model Summary
          R       R-sq          F        df1        df2          p
      .6309      .3981   174.5956     1.0000   264.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant     2.7413      .1882    14.5695      .0000     2.3708     3.1117
IPSI          .2357      .0178    13.2135      .0000      .2006      .2709
**************************************************************************
Outcome: MCD
Model Summary
          R       R-sq          F        df1        df2          p
      .2742      .0752    21.4596     1.0000   264.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant     4.7832      .2711    17.6435      .0000     4.2494     5.3170
IPSI         -.1191      .0257    -4.6324      .0000     -.1697     -.0685
**************************************************************************
Outcome: AI
Model Summary
          R       R-sq          F        df1        df2          p
      .6725      .4522    72.1035     3.0000   262.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant     1.2955      .3685     3.5152      .0005      .5698     2.0212
MCS           .5802      .0657     8.8283      .0000      .4508      .7096
MCD           .0828      .0456     1.8150      .0707     -.0070      .1726
IPSI          .0916      .0240     3.8123      .0002      .0443      .1389
************************** TOTAL EFFECT MODEL ****************************
Outcome: AI
Model Summary
          R       R-sq          F        df1        df2          p
      .5378      .2892   107.4381     1.0000   264.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant     3.2819      .2223    14.7612      .0000     2.8441     3.7197
IPSI          .2185      .0211    10.3652      .0000      .1770      .2600

***************** TOTAL, DIRECT, AND INDIRECT EFFECTS *******************

Total effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .2185      .0211    10.3652      .0000      .1770      .2600

Direct effect of X on Y
     Effect         SE          t          p       LLCI       ULCI
      .0916      .0240     3.8123      .0002      .0443      .1389

Indirect effect of X on Y
```

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.1269	.0258	.0800	.1805
MCS	**.1368**	.0249	.0914	.1895
MCD	**-.0099**	.0056	-.0243	-.0011
(C1)	**.1466**	.0253	.1012	.2003

Partially standardized indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.0965	.0186	.0609	.1347
MCS	.1040	.0180	.0713	.1415
MCD	-.0075	.0044	-.0186	-.0008

Completely standardized indirect effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.3124	.0565	.2065	.4293
MCS	.3366	.0546	.2376	.4515
MCD	-.0243	.0143	-.0617	-.0025

Ratio of indirect to total effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	.5808	.1260	.3628	.8571
MCS	.6259	.1276	.4098	.9136
MCD	-.0451	.0281	-.1212	-.0047

Ratio of indirect to direct effect of X on Y

	Effect	Boot SE	BootLLCI	BootULCI
TOTAL	1.3854	15.3268	.5627	5.8290
MCS	1.4930	16.5790	.6378	6.2657
MCD	-.1076	1.2739	-.4746	-.0075

Normal theory tests for specific indirect effects

	Effect	**se**	**Z**	**p**
MCS	**.1368**	**.0187**	**7.3262**	**.0000**
MCD	**-.0099**	**.0059**	**-1.6568**	**.0976**

Specific indirect effect contrast definitions
(C1) MCS minus MCD

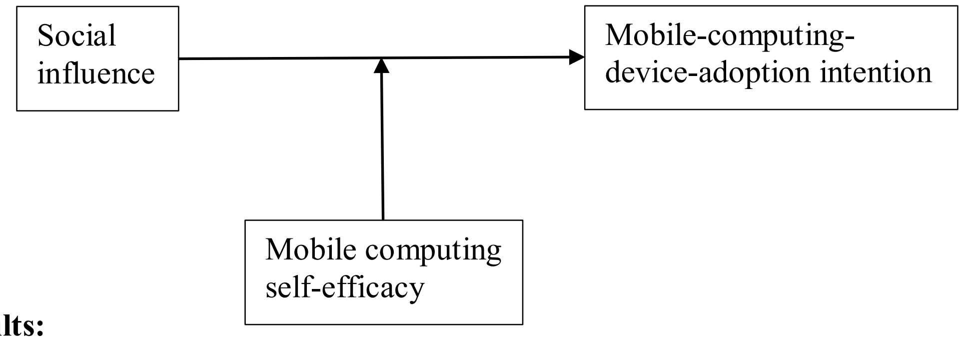
******************** ANALYSIS NOTES AND WARNINGS *************************

Number of bootstrap samples for bias corrected bootstrap confidence intervals:
5000

Level of confidence for all confidence intervals in output:
95.00

------ END MATRIX -----

3. Moderation Analysis:



Results:

```
***************** PROCESS Procedure for SPSS Release 2.10 ****************

          Written by Andrew F. Hayes, Ph.D.       www.afhayes.com
    Documentation available in Hayes (2013). www.guilford.com/p/hayes3

**************************************************************************
Model = 1
    Y = AI
    X = SI
    M = MCSE
Sample size
        266
**************************************************************************
Outcome: AI
Model Summary
          R       R-sq          F        df1        df2          p
      .7359      .5416   103.1822     3.0000   262.0000      .0000
Model
              coeff         se          t          p       LLCI       ULCI
constant     5.4215      .0590    91.9329      .0000     5.3053     5.5376
MCSE          .8040      .0490    16.4180      .0000      .7076      .9005
SI           -.1249      .0486    -2.5701      .0107     -.2205     -.0292
int_1         .0738      .0293     2.5196      .0123      .0161      .1315

Interactions:
 int_1    SI          X     MCSE
R-square increase due to interaction(s):
         R2-chng          F        df1        df2          p
int_1      .0111     6.3485     1.0000   262.0000      .0123
*************************************************************************
Conditional effect of X on Y at values of the moderator(s):
       MCSE     Effect         se          t          p       LLCI       ULCI
    -1.9261     -.2670      .0879    -3.0386      .0026     -.4400     -.0940
     -.9261     -.1932      .0644    -3.0015      .0029     -.3200     -.0665
      .4073     -.0948      .0452    -2.0982      .0368     -.1838     -.0058
     1.0739     -.0456      .0462     -.9875      .3243     -.1366      .0454
     1.7406      .0036      .0547      .0651      .9481     -.1041      .1112

Values for quantitative moderators are 10th, 25th, 50th, 75th, and 90th
percentiles.
********************* JOHNSON-NEYMAN TECHNIQUE *************************
Moderator value(s) defining Johnson-Neyman significance region(s):
```

Value	% below	% above
5.4218	**61.2782**	**38.7218**

Conditional effect of X on Y at values of the moderator (M)

MCSE	Effect	se	t	p	LLCI	ULCI
1.0000	-.4146	.1415	-2.9299	.0037	-.6932	-.1360
1.3000	-.3924	.1332	-2.9465	.0035	-.6547	-.1302
1.6000	-.3703	.1249	-2.9638	.0033	-.6163	-.1243
1.9000	-.3482	.1168	-2.9814	.0031	-.5781	-.1182
2.2000	-.3260	.1087	-2.9991	.0030	-.5401	-.1120
2.5000	-.3039	.1008	-3.0160	.0028	-.5023	-.1055
2.8000	-.2818	.0930	-3.0308	.0027	-.4648	-.0987
3.1000	-.2596	.0854	-3.0415	.0026	-.4277	-.0915
3.4000	-.2375	.0780	-3.0446	.0026	-.3911	-.0839
3.7000	-.2153	.0710	-3.0343	.0027	-.3551	-.0756
4.0000	-.1932	.0644	-3.0015	.0029	-.3200	-.0665
4.3000	-.1711	.0584	-2.9317	.0037	-.2860	-.0562
4.6000	-.1489	.0531	-2.8043	.0054	-.2535	-.0444
4.9000	-.1268	.0489	-2.5933	.0100	-.2231	-.0305
5.2000	-.1047	.0460	-2.2757	.0237	-.1952	-.0141
5.4218	**-.0883**	**.0448**	**-1.9691**	**.0500**	**-.1766**	**.0000**
5.5000	-.0825	.0447	-1.8481	.0657	-.1705	.0054
5.8000	-.0604	.0450	-1.3412	.1810	-.1490	.0283
6.1000	-.0383	.0471	-.8128	.4171	-.1309	.0544
6.4000	-.0161	.0506	-.3187	.7502	-.1157	.0834
6.7000	.0060	.0553	.1090	.9133	-.1028	.1148
7.0000	.0282	.0609	.4627	.6440	-.0917	.1480

******************** ANALYSIS NOTES AND WARNINGS *************************

Level of confidence for all confidence intervals in output:
95.00
------ END MATRIX -----

VITA

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Education

The University of Mississippi, University, MS
PhD in Business Administration – MIS
August 2014 GPA: 3.74

Missouri State University, Springfield, MO
Master of Business Administration focused on **Computer Information Systems**
December 2009 GPA: 3.60

Beijing University of Aeronautics and Astronautics (Beihang University), Beijing, China
Bachelor of Engineering, major in **Computer Science and Technology,** focused on **Data Mining and Database Management**
July 2007 GPA: 3.25

Publications

Conference Proceedings

Guo, X. and Díaz López, A. "Mobile Decision Support System Usage in Organizations," the 19th Americas Conference on Information Systems (AMCIS), Chicago, IL, August 2013.

Díaz López, A., Guo, X., and Pumphrey, D. "Multidimensional Charts," the 19th Americas Conference on Information Systems (AMCIS), Chicago, IL, August 2013.

Guo, X. and Reithel, B. "Assessing the Utility of Mobile Computing Devices at Work: the Information Processing Support Index," to be presented at the 20th Americas Conference on Information Systems (AMCIS), Savannah, GA, August 2014.

Presentations

Reithel, B. and Guo, X. "Crimi
nals in the Clouds" the FBI's 2014 Mississippi Digital Forensics Conference, Ridgeland, MS, May 7, 2014

Working Papers

Reithel, B., Pumphrey, D, Guo, X., & Mukhopadyay, S. "Counterproductive spoliation behavior of I.S. professional in eDiscovery"

Guo, X. "A framework for assessing infor
mation security levels"

Guo, X. "Mobile devices adoption in organizations, a cross-cultural examination"

Guo, X. "Mobile computing devices at work"

Guo, X. "The determinants of capital structure choice: An artificial neural network approach"

Undergraduate Thesis

Guo, X. "An Association Rule Based Webpage Pre-fetching Model: Design and Implementation," 2007.

Dissertation

Title: Mobile computing device adoption in organizations: an information-processing based view

Abstract: Mobile computing devices are proliferating in today's organizations. The two major purposes of this study are to create a new multi-item instrument, information-processing support index (IPSI) to measure how well mobile devices support employees' job required information-processing activities and to propose a conceptual model of mobile device adoption intentions in organizations. The IPSI instrument is developed by following the scale development literature. It provides interesting insights about how mobile devices differ in terms of their ability to support the two aspects of information processing: content generation and consumption. I have finished my instrument refinement process, pilot study, proposal defense, and main data collection and analysis. The pilot study results provide some initial support for the conceptual model, which includes a positive relationship between the IPSI and people's mobile-computing-device-adoption intentions. The main study survey questionnaires were distributed to faculty and staff members in one public university in China to gather further empirical support for my model. A double translation process was conducted to ensure the quality of the survey response. The main data analysis showed some empirical support for the hypotheses in my model.

Research Interests

My broad research interests are in information system adoption, information system security, information assurance, and privacy. Currently, I am working on building a portfolio of mobile computing-related research. By following the development of Information Processing Support Index (IPSI) framework, I plan to examine various factors affecting individual-level information systems adoption behavior. I also plan to conduct research in the information security area including digital forensics, network security, privacy, and organization security policies. My prior background and research include data mining, database management, neural networks, and network security.

Teaching Experience

Classes Taught:

MIS 309, Management Information Systems, University of Mississippi, Fall, 2012

MIS 309, Management Information Systems, University of Mississippi, Spring, 2013

Teaching Assistant:
MIS 309, Management Information Systems, University of Mississippi, Fall, 2013
MIS 419, Applications of Management Information Systems, University of Mississippi, Spring, 2014

Academic Affiliations

Member, Association for Information Systems (since 2012)
Member, Association for Computing Machinery (since 2013)
Reviewer, Americas Conference on Information Systems (AMCIS) 2013, 2014; International Conference on Information Systems (ICIS) 2013
Participant, AMCIS 2013 Doctoral Consortium
Participant, SWDSI 2014 Doctoral Consortium

Work Experience

School of Business Administration, University of Mississippi, University, MS, Currently
Research Assistant

- Provided research assistant to faculty member on information security and information assurance related areas.

Graduate Instructor

- Taught MIS 309 Management Information Systems for fall 2012 and spring 2013 semesters.

Extended Campus, Missouri State University, Springfield, MO, 2008 - 2011
Graduate Assistant

- Provided technical assistance to faculty, staff, and administrative personnel related to the university's online programs
- Supported the Extended Campus by providing microcomputer support for the staff and serving as liaison between the staff and computer services.

Springfield area Chamber of Commerce, Springfield, MO, 2009 - 2010
Internship

- Internship at international business council of Springfield area Chamber of Commerce, responsibilities including conducting background research on prospective Chinese companies and providing language support.

Chinese Students and Scholars Association (CSSA), Missouri State University, Springfield, MO, 2008 - 2011
Webmaster

- Managed information distribution among all CSSA members
- Maintained the CSSA Website: Association of Chinese Students and Scholars
- Set up and maintain the online Forum http://cssamsu.cool5site.net/forum.htm
- Organized Chinese New Year Banquet, Moon Festival Party and other activities in CSSA

Springfield ReManufacturing Corp., Springfield, MO, 2007 - 2010
Translator/Interpreter

- Provided translation services for visiting Chinese delegations.

Awards:

- Outstanding Undergraduate Student of Universities in Beijing, China, 2007
- Second prize in the 17th "Feng Ru Cup" student technology innovation competition of Beihang University, Beijing, China, 2007
- People's Scholarship, Beijing, China, 2006

Technical Skills:

- **Programming languages:** Java, C++, Visual Basic
- **Database management systems:** Microsoft Access, SQL
- **Operating systems:** Windows 95/98/2000/XP/Vista/7
- **Scripting languages:** HTML, XML, CSS, PHP
- **Statistical Packages:** SPSS, AMOS, SAS, S plus
- **Network administration:** Ethernet, TCP/IP, PGP, Network Security
- **Other:** Microsoft Office, Project, Visio, Artificial Neural Networks